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XU, Sijia; SHONCHOY, Abu S.; and FUJII, Tomoki. Illusion of gender parity in education: Intrahousehold resource allocation in Bangladesh. (2019). 09-2019, 1-70. Research Collection School Of Economics.
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SMU ECONOMICS & STATISTICS

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April 2019

Paper No. 09-2019

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THE SCHOOL OF ECONOMICS, SMU

Illusion of Gender Parity in Education: Intrahousehold Resource Allocation in Bangladesh*

Sijia Xu†, Abu S. Shonchoy‡, Tomoki Fujii§

April 26, 2019

Abstract

A target in the Millennium Development Goals—gender parity in all levels of education—is widely considered to have been attained. However, measuring gender parity only through school enrollment is misleading, as girls may lag behind boys in other educational measures. We investigate this with four rounds of surveys from Bangladesh by decomposing households' education decisions into enrollment, education expenditure, and share of the education expenditure allocated for the quality of education like private tutoring. We find a strong profemale bias in school enrollment but promale bias in the other two decisions. This *contradirectional* gender bias is unique to Bangladesh and partly explained by the presence of conditional cash transfer programs. Although these programs promoted girls' enrollment in secondary schools, they were largely ineffective in narrowing the gender gaps in academic performance and intrahousehold allocation of education resources. Gender parity in education cannot be truly achieved without addressing these gaps.

JEL Classification: D15, I28, J16, O15

Keywords: Female Stipend Programs; education; conditional cash transfer; private tutoring; Bangladesh

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*We are very grateful to IDE-JETRO for providing funding for this research. We would like to thank Sonia Akter, Niaz Asadullah, Yvonne Jie Chen, Xiaoping Chen, Namrata Chindarkar, Hai-Anh H. Dang, Isaac Ehrlich, Andrew Francis-Tan, Nobu Fuwa, Tatsuo Hatta, Christine Ho, Charles Yuji Horioka, Ravi Kanbur, Cem Karayalcin, Jong-Wha Lee, Jing Li, Peng Liu, Norihiko Matsuda, Sunha Myong, Manabu Nose, Yohanes Eko Riyanto, Yasuyuki Sawada, Yoshito Takasaki, Long Q. Trinh, Wuyi Wang, Jingyi Xue, Jubo Yan, Naoyuki Yoshino, and participants at seminars and workshops organized by the University of Tokyo, the National University of Singapore, the Asia Growth Research Institute and the Asian Development Bank Institute, Australasian Development Economics Workshop, China Meeting of the Econometric Society, NEUDC Conference: Cornell University, Nanyang Technological University, and Florida International University for their comments and inputs.

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1 Introduction

The last several decades have observed significant progress in education around the globe. A majority of children in the developing world, including those with disadvantaged backgrounds, have at least some education today. Notably, the spread of education for girls—who were historically disadvantaged—has outpaced that for boys in recent years. By 2015, five out of the nine developing regions had achieved gender parity in primary school enrollment. Other regions had also substantially narrowed the gender gap. There were 103 girls for every 100 boys enrolled in primary schools in 2015 in Southern Asia, up from only 74 in 1990. Indeed, Target 3. A of the Millennium Development Goals—gender equality in all levels of education—is widely accepted to have been achieved (United Nations, 2015). The achievement of gender parity in enrollment is a significant milestone, particularly given the positive multiplier or "ripple" effects of girls' education in all sectors of development (Glewwe and Kremer, 2006).

Developing countries' dedication of local resources coupled with effective use of donor assistance enabled this achievement. Education programs have often been targeted at the groups who are underprivileged and lagging behind, such as girls and children from poor households. One notable example is conditional cash transfer (CCT) programs. These programs incentivize households to send children to school by giving cash to eligible households fulfilling certain conditions such as satisfactory school attendance. For example, the pioneering CCT program, Progresa in Mexico, has substantially raised secondary school enrollment for girls and reduced the gender gap in schooling in rural areas (Dubois et al.,2012). The Progresa's success has motivated many other countries to adopt CCT programs, which helped those who have been disadvantaged catch up with the rest (See, Fiszbein and Schady (2009) for a comprehensive review).

Nevertheless, looking at gender parity in education only through the narrow lens of school enrollment may only lead to an illusion of success. Girls may lag behind boys in other important educational outcomes, even when gender parity in school enrollment is achieved. For example, strong gender preference for boys may bias intrahousehold allocation of education resources. This, in turn, may lead to a systematic gender gap in education quality and performance. Therefore, households' responses to CCT programs and children's school performance must be taken into account to holistically assess the progress towards gender parity in education, an important issue mostly ignored in the existing literature. We explore this issue using household survey data from Bangladesh with detailed information on education expenditure. We show that a sizable and statistically significant gender gap—conditional on enrollment—persisted in the intrahousehold allocation of education resources, which appears to have led to a gender gap in school performance.

Bangladesh, a predominantly patriarchal country, has achieved a remarkable progress in bringing children to school. The recent progress is especially pronounced at the secondary level. The gross secondary school enrollment rate for boys [girls] increased from 27 percent [14 percent] in 1990 to 66 percent [72 percent] in 2016. This noteworthy progress has been supported by a number of interventions implemented by governmental and nongovernmental organizations (See Ahmed et al.(2007) for a review). In particular, interventions targeted to promote girls' education have helped eliminate or reverse the gender gap in education in Bangladesh (Ahmed et al., 2007; Chowdhury et al., 2002; Shafiq, 2009). At the secondary level, the Female Stipend Programs (FSPs)—CCT programs that provide girls with a stipend and tuition fee waiver—have been especially credited for narrowing the gender gap in enrollment (Asadullah and Chaudhury, 2009; Behrman, 2015; Khandker et al., 2003; Mahmud, 2003; Begum et al., 2017).

Despite this progress, girls are lagging behind boys in various educational outcomes in the secondary and higher levels of education. As shown in Figure 1, girls consistently underperform boys, both in terms of passing rates and the share of top students in the Secondary School Certificate (SSC) examination— a national exam for secondary school completion. Girls also face higher rates of dropout and grade repetition than boys (Schurmann, 2009). If the gender difference in the enrollment rate is taken as a sufficient statistic for gender disparity in education, then this persistence of girls' underperformance in secondary education would be puzzling, given the reduction (and indeed reversal) of the gender gap in the secondary enrollment rate. This puzzle demonstrates the problem with focusing exclusively on gender parity in enrollment.

Many factors can potentially explain girls' underperformance in secondary education: low female ratio among teachers, unfavorable gender attitudes of teachers, and lack of gender-appropriate school curriculum and facilities (e.g., separate toilet facilities for boys and girls). These supply-side factors are relevant and have been studied at length in the literature. In comparison, the demand-side constraints that would potentially limit education policies and programs are relatively understudied. With this broader perspective, we investigate the gender gap from the demand side by highlighting the allocation of education expenditure within the household.

One methodological challenge in this research is the interdependence of the education decisions on whether to send a child to school, how much to spend on the child's education, and how to spend it. To address this challenge, we develop a three-part model consisting of three related education decisions of the household: 1) enrollment, 2) total education expenditure conditional on enrollment, and 3) share of the total education expenditure on the "core" component—which we argue directly affects the quality of the child's education and includes items such as tuition fee and private tutoring as elaborated in Section 4.

Figure 1: The performance at the Secondary School Certificate (SSC) examination by gender over time. The solid lines represent the proportions of boys (blue) and girls (red) who have passed the SSC examination among those who took the examination and the dashed lines represent the share of top students who achieved the highest grade point average (locally known as "GPA 5"). *Source: BANBEIS-Education Database* (http://data.banbeis.gov.bd/) accessed on Oct 29, 2017.

We then apply this three-part model to four rounds of nationally representative household surveys. We find a clear profemale bias in the enrollment decision. On the other hand, the decisions on the total education expenditure and core share—conditional on enrollment—are significantly promale in the recent three survey rounds. For example, girls were 12 percentage points more likely to be enrolled in secondary school than boys in 2010. However, conditional on enrollment, the total education expenditure and the expenditure on the core items for girls in 2010 were lower than those for boys by 617 BDT and 605 BDT [1]—about 8 percent and 12 percent of the total education expenditure and the expenditure on the core items for boys, respectively.

This *contradirectional* gender gap is unique to Bangladesh and noteworthy. In particular, existing studies in other South Asian countries such as India and Pakistan tend to find a promale gender gap as elaborated in the next section. Therefore, the natural question arises of why a contradirectional gender gap is only found in Bangladesh but not in other South Asian countries that have broadly similar cultural, political, and economic backgrounds and share historical roots with Bangladesh. Clearly, gender discrimination alone fails to explain what is observed in Bangladesh, because it would lead to a

[1]Based on the average exchange rate, 1 USD=70 BDT in 2010.

codirectional—and not contradirectional—gender gap.

To better understand the observed contradirectionality of gender gap in Bangladesh, we explore the relevance of the FSPs, because a comparable nationwide program did not exist in India or Pakistan during our study period. We find some evidence that the FSPs help explain this contradirectionality of gender gap. To be more specific, the FSPs were successful in increasing enrollment but not in narrowing the gender gap in education expenditure and core share conditional on enrollment. This indicates the presence of gender gap in the quality of education once children are in school. Therefore, while CCT programs like the FSPs can be effective in bringing girls to school and help improve or even reverse the gender gap in the quantity of education, they may be ineffective in narrowing the gender gap in the amount and kind of education resources given to children. Even though policies to narrow the gender gap in the quantity of education are desirable, policymakers may also need to consider implementing complementary policies, such as school quality improvement programs and vouchers for free supplementary or remedial education to improve the quality of education for girls.

The rest of this paper is organized as follows. We review related studies and discuss our paper's relevance and contributions to the body of existing studies in Section 2. We introduce the three-part model in Section 3, followed by the data description and key summary statistics in Section 4. In Section 5, we document the contradirectional gender gap using the three-part model. We then investigate the relevance of the FSPs to the contradirectionality of the gender gap in Section 6. We offer a diagrammatical analysis to explain our findings coherently and explore the relevance of our findings to the labor market returns in Section 7. Some discussions are provided in Section 8.

2 Relevance and Contributions to Existing Literature

This study contributes to the literature on intrahousehold allocation of resources for human capital investment in developing countries. Previous studies highlighted a gender bias whereby parents systematically invest more resources on sons' education (e.g., Deaton (1989), Li and Tsang (2003)).
Employing a hurdle model, Kingdon (2005) find a promale bias in the enrollment decision, but no evidence of a gender bias in education expenditure among enrolled children in rural India. Azam and Kingdon (2013) revisit this study with more comprehensive data from India and find that the promale bias has persisted. This finding is further supported by Majumder et al. (2016) using Heckman's two-step model in West Bengal and Saha (2013) using the Oaxaca-Blinder decomposition.

Besides India, the hurdle model has also been applied to other countries, including Malaysia (Kenayathulla, 2016), Pakistan (Aslam and Kingdon, 2008), Paraguay (Masterson, 2012), and Sri Lanka

Table 1: Existing studies on gender gap in education expenditure using a hurdle model

Study	**Location & Year**	**Age Grp**	**Enroll**	**Cond. Exp.**
Kingdon (2005)	16 states in rural India, 1994	5 to 14	−	≈
Aslam and Kingdon (2008)	Pakistan, 2001-02	5 to 9 10 to 14	− −	≈ −
Himaz (2010)	Sri Lanka, 1990-91, 1995-96, 2000-01	5 to 9 10 to 13 14 to 16	≈ ≈ ≈	+ ≈ +
Masterson (2012)	Rural Paraguay, 2000-01 Urban Paraguay, 2000-01	5 to 14 5 to 14	− +	− +
Azam and Kingdon (2013)	India, 2004-05	5 to 9 10 to 14	≈ −	− −
Kenayathulla (2016)	Malaysia, 2004-05	5 to 14	≈	≈

Note: −, + and ≈ mean promale bias, profemale bias and no bias, respectively.

(Himaz, 2010). The main results of the aforementioned studies using a hurdle model are summarized in Table 1. For example, Aslam and Kingdon (2008) find that there is a significant promale bias in enrollment decision for children aged 5-9 and 10-14 in Pakistan. However, a promale bias in education expenditure conditional on enrollment is found only for children aged 10-14.

Table 1shows that promale bias is far from ubiquitous; Masterson (2012) find promale bias in rural areas but profemale bias in urban areas in Paraguay. In Malaysia, no gender gap was found (Kenayathulla, 2016), whereas profemale bias was also detected in Sri Lanka (Himaz, 2010). Wongmonta and Glewwe (2017) also find a gender gap in favor of females in Thailand, though not based on a hurdle model. Table 1also shows that the directions of gender biases in enrollment and conditional education expenditure decisions are never contradirectional (i.e., if one of them is significantly profemale [promale], then the other is never significantly promale [profemale]).

Therefore, the contradirectional gender bias documented in detail below is new. It is notable that the contradirectional gender bias in Bangladesh contrasts with a clear (codirectional) promale bias in India and Pakistan, particularly for the older age group. The contradirectional bias is important because it is persistent and prevalent. It is clearly present since 2000 and found both in urban and rural areas. The evidence for the presence of the contradirectional bias is also robust. In particular, it is still detected even after taking into account the gender difference in the intrahousehold competition among siblings.

This paper also makes a modest methodological contribution by extending the hurdle model to include a third equation for the core share in the total education expenditure. This additional equation enables us to detect the gender bias in the way education expenditure is used. Furthermore, we allow for correlations in the unobservable error terms across different decisions. By taking advantage of this correlational structure, we are potentially able to obtain more accurate estimates than the equation-by-equation regressions widely used in the literature.

This paper also contributes to the growing literature on the impact of CCT programs. CCT programs are found to be effective in promoting school enrollment for the targeted population (e.g., Khandker et al. (2003); Mahmud (2003); Glewwe and Kassouf (2012); Behrman et al. (2009)), though they may not help to improve education quality as shown in Mexico (Behrman et al.,2009), Bangladesh (Khandker et al., 2003), and Brazil (Glewwe and Kassouf, 2012). The impact of CCT on test scores, as a measure of educational performance, is weak at best (Saavedra and García, 2012). We offer a new angle in this literature by examining the allocation of education resources within the household in the presence of a CCT program.[2]

Consistent with previous studies, we find that CCT programs were effective in bringing girls to schools. However, they did not attract a sufficient amount of complementary investment from the household. The gap between enrolled boys and girls in school performance did not narrow as a result. While our analysis is based only on Bangladeshi data, the lack or inadequacy of complementary investment from the household may be among the important reasons why CCT programs did not achieve notable improvements in educational outcomes beyond attendance. Thus, this study offers a cautionary lesson to researchers and policymakers that simply increasing the enrollment of female students does not automatically narrow the gender gap in the quality of education that children receive.[3]

Beyond the empirical findings discussed above, we offer some plausible explanations why there is a lack of complementary investment from the households with a simple diagrammatic model of the market for education quality and discuss the relevance of labor market returns. While these explanations are somewhat speculative due to the lack of data, they may offer some guidance to policymakers and researchers where challenges may exist in reducing the gender gap in the quality of education.

3 The Three-Part Model

We extend the hurdle model proposed in Kingdon (2005)—a model consisting of decisions on the child's school enrollment and the amount of education expenditure conditional on enrollment—in two

[2]Note also that there are a number of studies that have examined the impact of CCT programs on noneducational outcomes such as health and cognitive abilities (Gertler, 2004; Fernald et al., 2008; Orazio et al., 2010; Paxson and Schady, 2010; Macours et al., 2012). While noneducational outcomes are also important, they are beyond the scope of this study.

[3]A related point was made in Shonchoy and Rabbani (2015). However, we provide more complete and coherent explanations of this phenomenon with a more rounds of survey data. Unlike Shonchoy and Rabbani (2015), we also investigate the gender differences in educational performance and investigate the relevance to the labor market returns.

directions. First, we extend the hurdle model to account for the gender difference in the way the education expenditure is used, a point that is mostly neglected in the literature. To see the relevance of this point, first consider a household with a boy and a girl in which an equal amount is spent on their education. Suppose further that the education expenditure for the boy is mostly used to pay for private tutoring, whereas that for the girl is mostly used to buy better or more uniforms. This gender difference in the pattern of education expenditure would result in a gender difference in the quality of education. To address this point, we classify education expenditure items into the core and peripheral components, where the former directly relates to the quality of education but the latter does not, as detailed in the next section. We then incorporate the core share of education expenditure as the third part of the model.

Second, we allow for correlations in unobservable error terms across all equations. This is important because there may be some unobservable characteristics, which may affect all three decisions simultaneously. Take innate ability as an example. A smart child (with high innate intellectual ability) is arguably more likely to be enrolled in school due to high expected returns from education. However, the child may require less education expenditure from the household than a less smart counterpart, because of a lower need for private tutoring or a higher chance of receiving merit-based scholarships. At the same time, households may be more encouraged to invest in children with a higher ability to learn. Our model enables the data to tell the sign and size of the correlations among the unobservable error terms.

Formally, we consider the following three outcome variables: school enrollment ($d \in \{0, 1\}$), education expenditure ($y(> 0)$), and core share in education expenditure ($s \in [0, 1]$), and our three-part model has the following structure:

$$d = \mathbf{1}(x'_d\beta_d + \varepsilon_d > 0) \tag{1}$$

$$\log y = x'_y\beta_y + \varepsilon_y \tag{2}$$

$$s = \max(0, \min(1, x'_s\beta_s + \varepsilon_s)), \tag{3}$$

where $\mathbf{1}(\cdot)$ is an indicator function, and x, β, and s in each equation are the vector of covariates, its coefficient vector, and the idiosyncratic error term. The covariates include, among others, a dummy variable for girl to identify the gender effect. The observed share s is related to its latent variable $s^* \equiv x'_s\beta_s + \varepsilon_s$, and s is a truncated version of s^* from below at zero and from above at one. It should be noted that the education expenditure (y) and core share (s) are observable if and only if the child is enrolled in school (i.e., $d = 1$).

To allow for the dependency across the three equations, we assume that the error terms ε_d, ε_y, and ε_s have the following trivariate normal distribution:

$$\begin{bmatrix}\varepsilon_d \\ \varepsilon_y \\ \varepsilon_s\end{bmatrix} \sim N\left(\mathbf{0}, \begin{bmatrix}1 & \rho_{dy}\sigma_y & \rho_{ds}\sigma_s \\ \rho_{dy}\sigma_y & \sigma_y^2 & \rho_{ys}\sigma_y\sigma_s \\ \rho_{ds}\sigma_s & \rho_{ys}\sigma_y\sigma_s & \sigma_s^2\end{bmatrix}\right), \qquad (4)$$

where the variance of s_d can be assumed to be unity without loss of generality. In what follows, we denote the probability density function and cumulative density function (CDF) for a standard normal distribution by ϕ and Φ, respectively, and the CDF for a standard bivariate normal distribution by Ψ. There are four distinct cases to consider in this setup: 1) the child is not enrolled in school (d = 0), 2) the child is enrolled in school with all education expenditure going to the peripheral component (d = 1 and s = 0), 3) the child is enrolled in school with education expenditure going to both the core and peripheral components (d = 1 and 0 < s < 1), and 4) the child is enrolled in school with all education expenditure going to the core component (d = 1 and s = 1).[4]

Given the model structure described by eqs. (1)-(4), the log-likelihood l_i for child $i \in \{1, \cdots, N\}$ given the parameter vector $\theta \equiv [\beta_d, \beta_y, \beta_s, \sigma_y, \sigma_s, \rho_{dy}, \rho_{ds}, \rho_{ys}]'$can be written as follows:[5]

$$l_i(\theta) = 1[d_i = 0] \cdot l_i^1 + 1[d_i = 1, s_i = 0] \cdot l_i^2$$

$$+1[d_i = 1, 0 < s_i < 1] \cdot l_i^3 + 1[d_i = 1, s_i = 1] \cdot l_i^4,$$

where the log-likelihood l_i^j for case $j \in \{1,2,3,4\}$ is given by the following with $e_y \equiv \frac{\log(y) - x'_y\beta_y}{\sigma_y}$ and $e_s \equiv \frac{s - x'_s\beta_s}{\sigma_s}$:

[4]Cases 2) and 4) are relatively rare in our data, accounting for 0.27 percent and 0.22 percent of all observations across years, respectively.

[5]The detailed derivation of the likelihood function for each case is provided in Appendix A.

$$
\begin{cases}
l_i^1 & = \log\left[\Phi(-x'_{d_i}\beta_d)\right] \\
l_i^2 & = \log(\phi(e_{y_i})) - \log(y_i) - \log(\sigma_y) \\
& \quad +\log\left[\Psi\left(\frac{x'_{d_i}\beta_d+\rho_{dy}e_{y_i}}{\sqrt{1-\rho_{dy}^2}}, -\frac{x'_{s_i}\beta_s+\rho_{ys}\sigma_s e_{y_i}}{\sigma_s\sqrt{1-\rho_{ys}^2}}, \frac{\rho_{dy}\rho_{ys}-\rho_{ds}}{\sqrt{(1-\rho_{dy}^2)(1-\rho_{ys}^2)}}\right)\right] \\
l_i^3 & = \log\left(\phi\left(\frac{e_{y_i}}{\sqrt{1-\rho_{ys}^2}}\right)\right) + \log\left(\phi\left(\frac{e_{s_i}}{\sqrt{1-\rho_{ys}^2}}\right)\right) \\
& \quad + \left(\rho_{ys}\frac{e_{y_i}e_{s_i}}{1-\rho_{ys}^2}\right) - \log(y_i) - \log(\sigma_y) - \log(\sigma_s) - \log\left(\sqrt{1-\rho_{ys}^2}\right) \\
& \quad +\log\left[\Phi\left(\frac{x'_{d_i}\beta_d(1-\rho_{ys}^2)+(\rho_{dy}-\rho_{ds}\rho_{ys})e_{y_i}+(\rho_{ds}-\rho_{dy}\rho_{ys})e_{s_i}}{\sqrt{(1-\rho_{ys}^2-\rho_{dy}^2-\rho_{ds}^2+2\rho_{dy}\rho_{ds}\rho_{ys})(1-\rho_{ys}^2)}}\right)\right] \\
l_i^4 & = \log(\phi(e_{y_i})) - \log(y_i) - \log(\sigma_y) \\
& \quad +\log\left[\Psi\left(\frac{x'_{d_i}\beta_d+\rho_{dy}e_{y_i}}{\sqrt{1-\rho_{dy}^2}}, \frac{x'_{s_i}\beta_s-1+\rho_{ys}\sigma_s e_{y_i}}{\sigma_s\sqrt{1-\rho_{ys}^2}}, \frac{\rho_{ds}-\rho_{dy}\rho_{ys}}{\sqrt{(1-\rho_{dy}^2)(1-\rho_{ys}^2)}}\right)\right].
\end{cases}
$$

The sample log-likelihood function is just the summation of individual log-likelihood function. Therefore, the maximum-likelihood (ML) estimator $\hat{\theta}_{ML}$ for the three-part model can be written as follows:

$$\hat{\theta}_{ML} = \underset{\theta}{\operatorname{argmax}} \sum_{i=1}^{N} l_i(\theta).$$

The primary coefficients of interest are those on the girl dummy in β_d, β_y, and β_s. If these coefficients have positive [negative] signs, they indicate a profemale [promale] bias. It should be noted here that the size of the coefficient does not necessarily equate with the size of the effect, because the model is nonlinear. Therefore, using the ML estimates, we calculate the marginal effects of being a girl on the probability of enrollment as well as conditional and unconditional levels of the total education expenditure and core expenditure. Because we cannot obtain a simple closed-form solution for the marginal effect due to the correlation across error terms, we need to use numerical integration to calculate marginal effects. The girl effects on d, y, and s are computed as the change in the expected value of the outcome of interest when the value of the girl dummy variable changes from zero to one, where we use the following expressions for the conditional and unconditional expectations:

$E(d) = P(d = 1) = \Phi(x'_d\beta_d)$ (Expected enrollment)

$E(y|d = 1) = \int_0^\infty yf(y|d = 1)dy$ (Conditional expected education expenditure)

$E(y) = P(d = 1)E(y|d = 1)$ (Unconditional expected education expenditure)

$E(ys) = \int_0^1 \int_0^\infty ysf(y, s)dyds$ (Unconditional expected core expenditure)

$E(ys|d = 1) = \frac{E(ys)}{P(d=1)} = \frac{E(ys)}{\Phi(x'_d\beta_d)}$ (Conditional expected core expenditure)

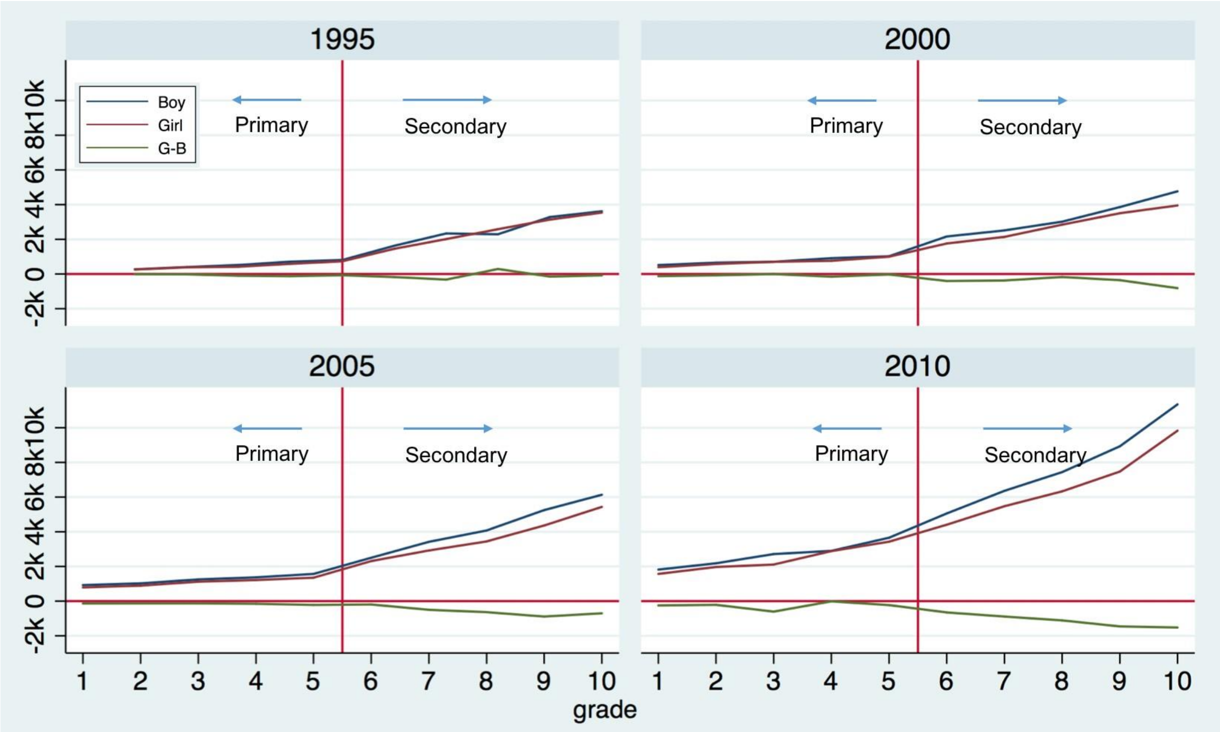

Figure 2: Nominal education expenditure in BDT by year, gender, and grade

where $f(y, s)$ is the joint probability density function for y and s, and the subscript i is omitted for simplicity. We use simulations to compute the standard errors for the equations above and evaluate only at the sample means to reduce the computational burden of numerical integrations.[6]

4 Data

We primarily use the nationally representative Household Expenditure Survey (HES) for the year 1995 and Household Income Expenditure Survey (HIES) for the years 2000, 2005, and 2010, all of which were conducted by the Bangladesh Bureau of Statistics. These datasets provide demographic and socioeconomic characteristics of the household and detailed information on education expenditure for each child in the household.[7]

Figure 2 depicts the average education expenditure conditional on enrollment for boys and girls and their difference for each grade, including both the primary (grades 1-5, officially ages 6-10) and secondary (grades 6-10, officially ages 11-15) levels.[8] There are three points to note from this figure. First, across all survey years, the education expenditure increases with grade, particularly from the secondary level.

[6]The details of the mathematical expressions used for numerical integrations and the simulation method for computing the marginal effects are described in Appendix B.

[7]Top one percent observations with the highest total educational expenditure are dropped as outliers. Further, to apply the three-part model to the data, we choose to drop from our sample around 0.39 percent of children who were enrolled in secondary school with no education expenditure. As a result, the education expenditure for a child in our sample is always positive (i.e., $y > 0$) whenever the child is enrolled in school (i.e., $d = 1$).

[8]Secondary education is sometimes subdivided into junior secondary (grades 6-8, officially ages 11-13) and secondary (grades 9-10, officially ages 14-15) levels in Bangladesh. We do not make this distinction.

Second, boys receive a larger investment in education than girls conditional on enrollment. Third, except for the year 1995, the gender gap in education expenditure tends to widen as the grade progresses, especially at the secondary level.

Therefore, secondary education appears to be particularly important for the analysis of gender gap. It is also worth noting that the gender policies of government interventions are different between the primary and secondary levels. The FSPs were targeted only at girls in secondary schools, whereas the Food for Education program, started in 1993, and its successor, the Primary Education Stipend program, started in 2002, were not targeted by the child's gender. Furthermore, passing the SSC examination, which is held at the end of the secondary education, is a major milestone in the Bangladeshi education system.[9] For these reasons, we choose to focus on the secondary education.

We include the following basic covariates in each of the three equations (eqs. (1)-(3)) in all reported three-part regressions: the age and gender of the child, the age and gender of the household head, logarithmic household size, logarithmic expenditure per capita, the number of children, head's working status and religion, and parental education in years. In addition, we also include the urban dummy to capture the geographical heterogeneity in parental investment in children's education. The choice of these covariates are broadly consistent with existing studies such as Kingdon (2005), Aslam and Kingdon (2008), Masterson (2012), and Azam and Kingdon (2013).

Some covariates are assumed to affect some but not all outcomes. In eq. (1), the numbers of secondary schools and madrasas per thousand people in the area of residence are included in the set of covariates as measures of school accessibility in addition to the basic covariates discussed above. We argue that this is reasonable, because school accessibility would primarily affect the enrollment decision, particularly in developing countries where school infrastructure is inadequate. On the other hand, it would not heavily affect education expenditure once the type of school that the child goes to is controlled for.

To construct the accessibility measures, we compile the number of schools and madrasas at the district or subdivision level (district-level data from BANBEIS (1995), BANBEIS (2006), and BANBEIS (2010) for the years 1995, 2005, and 2010 and subdivision-level data from Bangladesh Bureau of Statistics (2002) for the year 2000) and divide by the population at that level using the population

[9] The analysis of older age groups, including the higher secondary and tertiary levels, are beyond the scope of this paper, because the analysis gets more complicated for three reasons. First, early marriage and pregnancy can result in grade repetition and dropout for girls, but we have only limited information about each child beyond gender and age. As a result, our three-part model cannot adequately address these issues and our estimates are likely to be confounded with early marriage and pregnancy. Second, the passing rate of the SSC examination was historically low, below 60 percent for most years before 2007 as Figure 1 shows. This makes it difficult to see whether the child is not in school because of not being able to pass the SSC or some other reasons. Finally, the proportion of girls in higher education was very small in earlier years, making it difficult to attain reliable estimates.

figures taken from the Population and Housing Census for the year 2001.[10]

In eq. (2), we add two school-type variables (public and private) as different types of schools may affect tuition, uniform, and other education expenditure differently.[11] The logarithmic education expenditure is separately added to control for the education expenditure in the core share equation (eq. (3)).

The upper part of Table 2 reports some descriptive summary statistics for the secondary school enrollment and its covariates in the secondary-school age group, disaggregated by the child's gender for the years 1995 and 2010. It shows impressive gains in a variety of development indicators between 1995 and 2010, including the enrollment rate, nominal household income, and mother's education. The bottom part of the table provides a breakdown of the school types among children who are enrolled in a secondary school.[12]

There are two important observations to make from Table 2. First, the first row shows that girls are on average more likely to be enrolled in secondary school than boys. The gender difference in enrollment was small and not significantly different from zero in 1995 even at a 10 percent level, but it has become larger and statistically significant since the year 2000. This is consistent with the common observation of the reversal of the gender gap from promale to profemale in school enrollment in Bangladesh in recent years (e.g., Asadullah and Chaudhury (2009)).

Second, Table 2 shows that there are some important differences between boys and girls in the demographic characteristics of the households they belong to. In particular, girls tend to live in a larger household than boys, and this difference is observed for all rounds of the survey. We will revisit this point in the next section.

To apply the three-part model to data, we categorized the education expenditure items into core and peripheral components. We choose to include expenditures for tuition, private tutoring, and materials (e.g., textbooks, exercise books, and stationary) in the core component. The peripheral component includes all other items, including admission, examination, uniform, meals, transportation, and others, which would only have a marginal relevance to the quality of education at best.

Because the choice of items in the core component is not an obvious choice, let us explain the reasons

[10]In 1991, there were 5 divisions, 64 districts, and 486 subdistricts in Bangladesh (Bangladesh Bureau of Statistics,1994, Table 2.7). While subdivision is not a commonly used unit, Bangladesh Bureau of Statistics (2002) divides Bangladesh into 22 subdivisions.

[11]The base school type in the regressions reported in Section 5 is all schools other than public and private schools, which include NGO schools and madrasas. While the choice of school type is potentially important, we choose not to model it for two reasons. First, public secondary schools are rare in Bangladesh, which accounts for less than five percent of all secondary schools (BANBEIS, 1995, 2006, 2010). Second, there is a significant mismatch in the type distribution of secondary schools between the HIES data and other sources. The proportion of children in public schools in our data is around 20 percent, which is much higher than five percent or less reported by BANBEIS(1995, 2006, 2010) and Nath et al. (2008). This discrepancy may in part stem from the public nature of private schools in Bangladesh, where private school teachers are often paid by the government under the Monthly Pay Order scheme. It should also be noted that our results remain qualitatively similar even when the school-type variables are dropped from the regression.

[12]The summary statistics for the years 2000 and 2005 corresponding to Table 2 are reported in Table 16 in Appendix F.

Table 2: Summary statistics of basic covariates by gender for 1995 and 2010 (secondary-school age group)

	1995				2010			
	Boy (B)	**Girl (G)**	**G-B**	**All**	**Boy (B)**	**Girl (G)**	**G-B**	**All**
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All children aged 11-15								
Enrolled in secondary school	0.349	0.370	0.021	0.359	0.465	0.560	0.095	0.511
	(0.477)	(0.483)		(0.480)	(0.499)	(0.496)	***	(0.500)
Child’s age (yrs)	13.022	12.903	-0.119	12.966	12.980	12.896	-0.084	12.940
	(1.369)	(1.351)	***	(1.362)	(1.389)	(1.372)	**	(1.382)
HH per capita expenditure	10.222	11.512	1.290	10.832	28.434	28.659	0.225	28.543
(thousand BDT/year)	(8.062)	(11.161)	***	(9.673)	(19.044)	(21.466)		(20.248)
Household size	6.634	6.807	0.173	6.716	5.518	5.605	0.087	5.560
	(2.507)	(2.518)	**	(2.513)	(2.005)	(1.868)	*	(1.940)
Father’s education (yrs)	3.691	3.951	0.260	3.814	2.780	2.832	0.052	2.805
	(4.426)	(4.578)	**	(4.500)	(4.150)	(4.172)		(4.160)
Mother’s education (yrs)	1.960	2.262	0.302	2.103	2.484	2.579	0.095	2.530
	(3.085)	(3.347)	***	(3.215)	(3.595)	(3.674)		(3.633)
Number of children	3.658	3.794	0.136	3.722	2.932	3.036	0.104	2.982
	(1.862)	(1.913)	**	(1.888)	(1.438)	(1.444)	***	(1.442)
Urban	0.314	0.365	0.051	0.338	0.342	0.335	-0.007	0.339
	(0.464)	(0.482)	***	(0.473)	(0.474)	(0.472)		(0.473)
Female head	0.084	0.089	0.005	0.086	0.131	0.139	0.008	0.135
	(0.277)	(0.285)		(0.281)	(0.337)	(0.346)		(0.342)
Head is a wage worker	0.354	0.365	0.011	0.359	0.407	0.404	-0.003	0.405
	(0.478)	(0.482)		(0.480)	(0.491)	(0.491)		(0.491)
Head’s age (yrs)	46.466	46.556	0.090	46.508	47.142	46.827	-0.315	46.990
	(11.188)	(11.115)		(11.152)	(10.597)	(10.554)		(10.577)
Muslim	0.898	0.890	-0.008	0.894	0.898	0.887	-0.011	0.892
	(0.303)	(0.313)		(0.308)	(0.303)	(0.317)		(0.310)
Hindu	0.094	0.101	0.007	0.097	0.093	0.103	0.010	0.098
	(0.292)	(0.301)		(0.296)	(0.290)	(0.305)		(0.297)
Obs	2,641	2,370		5,011	3,209	2,996		6,205
Children aged 11-15 enrolled in a secondary school								
Govt school	0.16	0.18	0.02	0.17	0.23	0.20	-0.03	0.22
	(0.37)	(0.39)		(0.38)	(0.42)	(0.40)	*	(0.41)
Private school	0.79	0.81	0.02	0.80	0.70	0.69	-0.01	0.70
	(0.41)	(0.40)		(0.40)	(0.46)	(0.46)		(0.46)
Other school	0.05	0.01	-0.04	0.03	0.07	0.10	0.03	0.09
	(0.21)	(0.11)	***	(0.17)	(0.26)	(0.30)	***	(0.28)
Obs	921	877		1,798	1,493	1,679		3,172

Note: Standard deviations are reported in parentheses below the mean. ***, **, and * denote that the means for girls and boys are different at 1, 5, and 10 percent significance levels, respectively, by a *t*-test of equality of means. Other school includes all types of schools other than public and private schools, including religious schools (like madrasas) and NGO schools.

for including tuition, private tutoring, and materials in the core component. First, it is reasonable to include the tuition fee in the core component because it reflects, at least to some extent, the quality of education provided by schools in Bangladesh. If schools face some degree of competition, those schools which consistently provide only low-quality education at a high tuition will exit the market such that a positive correlation between the quality of education and tuition would emerge. The force of competition is likely to be important in Bangladesh where a large majority of secondary schools are private. Further, as elaborated in Appendix C, an analysis of a separate dataset shows a positive relationship between the average tuition fee and test score at the primary level, which serves as suggestive evidence that a higher tuition reflects higher quality of education.

Second, private tutoring is also a key item of the core component. It is widely documented that private tutoring can be an important educational input (Bray, 1999, 2003), because it is associated with better learning achievements for the students (Nath, 2012; Asadullah et al., 2018). This is also the case in Bangladesh (Nath, 2008; Hamid et al., 2009); it is not uncommon in Bangladesh for public school teachers to serve as private tutors for their students. In some cases, teachers may deliberately teach less in the regular classes to gain more incomes from private tutoring. Thus, there are good reasons to include private tutoring in the core component.

Nevertheless, the spending on private tutoring must be interpreted with caution. On one hand, private tutoring would raise the overall quality of education that the child receives. On the other hand, if private tutoring is given only to weaker students and boys are generally weaker than girls, the promale bias in the core share we show subsequently may be driven by the relatively weak academic performance of boys. We argue that this latter possibility is unlikely to be important, given that girls have underperformed boys in the passing rate and the share of top students in the SSC examination over years as shown in Figure 1.

Finally, it is also reasonable to include materials in the core component, because reading more textbooks and doing more exercises also directly contribute to the academic performance. However, one could argue that more expensive books are not necessarily of higher quality. Thus, the inclusion of materials in the core component is admittedly disputable. To address this concern, we also repeated the analysis in the next section excluding the materials from the core component (unreported). It turns out that the results are qualitatively similar. Thus, our results are not driven by the inclusion of the materials in the core component. In sum, our choice of the definition of the core component is reasonable, if not undisputable.

Table 3 reports summary statistics of education expenditure items in nominal terms for the years 1995 and 2010 using a subsample of children who were enrolled in secondary school at the time of

Table 3: Summary statistics of annual education expenditure in BDT by items for secondary school enrollees in 1995 and 2010

	1995				2010			
	Boy (B)	Girl (G)	G-B	% Zeros	Boy (B)	Girl (G)	G-B	% Zeros
Item	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Core	1,673	1,582	-91	1	5,239	4,285	-955	0
	(1,616)	(1,540)			(5,082)	(4,363)	***	
Tuition	275	194	-81	32	549	296	-253	46
	(313)	(305)	***		(963)	(606)	***	
Private Tutoring	803	789	-14	45	3,273	2,627	-647	26
	(1,298)	(1,226)			(4,335)	(3,745)	***	
Material	595	600	5	1	1,418	1,362	-55	1
	(429)	(415)			(950)	(929)	*	
Peripheral	717	747	30	1	2,110	2,067	-43	0
	(878)	(791)			(2,224)	(2,077)		
Admission	126	138	12	24	371	337	-35	21
	(211)	(197)			(657)	(561)		
Exam	115	124	9	5	301	295	-6	5
	(146)	(139)			(288)	(270)		
Uniform	215	249	34	45	619	630	11	19
	(290)	(278)	**		(534)	(658)		
Meal	40	5	-35	99	424	377	-47	58
	(464)	(58)	**		(806)	(744)	*	
Transportation	87	109	22	81	205	311	107	85
	(333)	(394)			(818)	(1,080)	***	
Others	133	122	-11	44	190	117	-73	75
	(281)	(344)			(1,273)	(776)	*	
Total	2,390	2,329	-61		7,349	6,352	-998	
	(2,112)	(2,030)			(6,151)	(5,524)	***	
Core Share	0.68	0.65	-0.03		0.67	0.63	-0.04	
	(0.19)	(0.20)	***		(0.18)	(0.19)	***	
Obs	921	877			1,493	1,679		

Note: Standard deviations are reported in parentheses below the mean. ***, **, and * denote that the means for girls and boys are different at 1, 5, and 10 percent significance levels, respectively. The summary statistics are for the subsample of the children who were enrolled in school at the time of survey. Core share stands for the ratio of core components over the total education expenditure. The annual session and registration fees are included in admission because they are not separately reported in HES 1995.

survey.[13] The italicized items below each of Core and Peripheral rows represent the underlying items in these component, respectively. As the bottom of the table shows, the average total education expenditure has rapidly increased between 1995 and 2010. Its annualized average growth rate in this period is 7.3 percent, which is substantially larger than the average annual inflation rate of 5.9 percent in consumer prices based on the World Development Indicators.

Table 3 also shows that the core component accounts for roughly two thirds of the total education expenditure and boys have a significantly higher core share than girls. Within the core component, private tutoring is the major expenditure item, but a considerable share of children have no spending on

[13]The same summary statistics for the years 2000 and 2005 are reported in Table 17 in Appendix F.

private tutor in both years. There is an obvious trend of increasing popularity in private tutoring over the years, particularly among higher grades. In 1995, 56 percent of male and 54 percent of female secondary school students reported to have spent a positive amount on private tutoring, but these ratios respectively increased to 78 percent and 71 percent in 2010. Further, among those with a positive spending on private tutoring, its share in the total education expenditure has also gone up slightly from 44 percent and 45 percent, respectively, for boys and girls in 1995 to 49 percent and 47 percent in 2010. Taken together, these show increasing dependency on private tutoring and increasing gender gap in the use of private tutoring, both in the intensive and extensive margins. Hence, parents are willing to invest more in children's, particularly boys', education for better quality of education beyond the basic educational costs like school fees.[14] It is also notable that girls on average have lower spending on tuition and a significant share of children have zero spending on tuition (32 percent in 1995 and 46 percent in 2010), which can be explained by the tuition waiver provided by various programs including the FSPs discussed in detail in Section 6.

5 Contradirectional Gender Gap

In this section, we document the persistent contradirectional gender gap using the three-part model developed in Section 3. We first present the ML estimates and then perform similar regressions under alternative specifications to show the robustness of our results. Finally, we compute the marginal effects of being a girl to provide estimates that have direct quantitative interpretations.

Estimation of coefficients

Table 4 presents the ML estimates of the coefficient on the girl dummy—the covariate of primary interest—in the three-part model for each year and for each of primary- and secondary-school age groups. Columns (1)-(3) are the estimates for the primary-school age group and columns (4)-(6) for the secondary-school age group. As the table shows, the significance of the gender gap for the primary age group is smaller both economically and statistically than that for the secondary-school age group, and thus we hereafter focus on the analysis of the secondary-school age group. While we allow for dependence in error terms, equation-by-equation regressions under the assumption that ρs are all zero yield similar results[15]

Column (4) of Table 4 shows the presence of clear and strong profemale bias in the enrollment decision from the year 2000 onwards, after controlling for the observables discussed in Section 4. That

[14]Of course, alternative interpretations are possible. For example, the increasing popularity of private tutoring may reflect the deteriorating quality in school education because of overcrowding of classrooms or teacher absenteeism (Banerjee and Duflo,2006).

[15]The results are presented in Table 19 in Appendix F.

Table 4: ML estimation of the three-part model by years and age groups

	Primary-school age (6-10)			**Secondary-school age (11-15)**		
	d	Cond *y*	Cond *s*	*d*	Cond *y*	Cond *s*
Coef.	(1)	(2)	(3)	(4)	(5)	(6)
1995						
Girl	-0.031	-0.013	-0.016	-0.001	-0.085***	0.001
	(0.036)	(0.033)	(0.012)	(0.042)	(0.032)	(0.032)
Obs.		6485			5011	
2000						
Girl	0.061*	-0.114***	0.009	0.339***	-0.174***	-0.082***
	(0.036)	(0.036)	(0.010)	(0.039)	(0.049)	(0.014)
Obs.		5600			4878	
2005						
Girl	0.048	-0.076**	-0.023**	0.291***	-0.154***	-0.071***
	(0.035)	(0.033)	(0.009)	(0.034)	(0.027)	(0.012)
Obs.		6481			5638	
2010						
Girl	0.134***	-0.066**	-0.019*	0.289***	-0.131***	-0.067***
	(0.032)	(0.029)	(0.010)	(0.033)	(0.025)	(0.009)
Obs.		7272			6205	

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. The estimation is based on the three-part model constructed in Section 3. In all regressions, the following covariates are also included: logarithmic per capita expenditure, logarithmic household size, father's and mother's education in years, number of children, female head, wage-worker head, head's age, and religion (muslim/hindu), urban area, and dummy variables for the child's age. In addition, the school accessibility variables, school-types dummy variables (public/private), and logarithmic education expenditure are also included in the equations for x_d, x_y, and x_s, respectively. Detailed results for secondary-school age group are presented in Table 18 in Appendix F.

is, other things being equal, parents are more likely to send girls to school than boys. Column (5) reveals that, conditional on enrollment, households spend significantly less on the secondary education of girls than that of boys in all the four survey rounds. Further, conditional on enrollment, the core component for girls tends to account for a lower share of the total education expenditure than that for boys as shown in column (6). Our analysis thus uncovers the presence of persistent contradirectional gender gap.

Columns (4)-(6) of Table 4 also appears to indicate that the gender gap in 1995 is somewhat different from the three more recent rounds. While we still see a promale bias in the conditional education expenditure, the coefficient on the girl dummy is substantially smaller in absolute value in 1995. Furthermore, the estimated coefficients on the girl dummy in the enrollment and core share equations are insignificant. We attempt to explain this observation in Sections 6 and 7.

Because the girl dummy is our main covariate of interest, we only presented its estimated coefficients in Table 4. The complete results of the regressions for secondary-school age group in Table 4 can be found in Table 18 in Appendix F. Here, we briefly summarize some notable findings about other covariates of interest. In general, children in richer households are more likely to be enrolled in school and receive a higher expenditure on education but a lower core share. Parental education, especially mother's education, has a qualitatively similar effect in all three decisions. The more educated parents are, the more likely children will enroll in school and the higher education expenditure they are likely to receive. In contrast, if the head is a wage worker, the child has a lower probability of enrollment but tends to receive a higher core share, except for the year 1995, after controlling for various covariates. These points appear to suggest the presence of positive intergenerational transmission in education. Somewhat surprisingly, the number of children has no effect as its coefficient is mostly insignificant.

Another notable finding is the relevance of the location of residence as well as school access and type. Children in rural areas are more likely to enroll in school but have a lower education expenditure conditional on enrollment, which may be a result of various aid programs targeted at rural areas. Table 18 also shows that children are more likely to enroll when the number of secondary schools per thousand people in the area of residence is higher. The coefficients on the school-type variables show that children going to private schools spend more on education than those going to public or other types of schools.

Robustness Checks

There is a potential endogeneity concern about the results in Table 4. To understand the endogeneity concern, recall from Table 2 that girls on average live in significantly larger households than boys. This may be explained by the fertility stopping rule with unobserved parental preference towards boys (Jensen,2002). If parents prefer to have a boy, they may continue to try to have more children until they have a boy. This will result in girls living in larger families than boys on average. Hence, the unobserved parental preference may simultaneously affect both the household's demographic composition as well as the education expenditure on children such that the unobserved error terms may be correlated with the covariates.

To partially address this concern, we include the household size and number of children in the set of covariates to control for the differences in the household composition in our regressions. However, these controls may not fully address the potential endogeneity concerns relating to the household composition. Therefore, as an alternative, we run linear regressions with household fixed effects to control for all household-level observable and unobservable characteristics in addition to the individual-level observable characteristics using a subsample of children from households with at least two children in the secondary-school age group. The signs of the coefficient on the girl dummy from these estimations are broadly consistent as Table 5 shows, though some coefficients are no longer statistically significant.

Table 5: Results of linear regressions with household-level fixed effects

Coef.	*d* (1)	Cond *y* (2)	Cond *s* (3)
1995			
Girl	-0.006	-0.139*	-0.014
	(0.028)	(0.076)	(0.027)
Obs	2,834	1,076	1,076
HHs	1,298	713	713
2000			
Girl	0.076***	-0.063	-0.043*
	(0.028)	(0.090)	(0.025)
Obs	2,695	1,015	1,015
HHs	1,258	693	693
2005			
Girl	0.098***	-0.032	-0.018
	(0.028)	(0.068)	(0.015)
Obs	2,587	1,084	1,084
HHs	1,220	736	736
2010			
Girl	0.095***	-0.078	-0.050***
	(0.031)	(0.061)	(0.019)
Obs	2,551	1,220	1,220
HHs	1,214	823	823

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors are reported in parentheses. Each point estimate corresponds to one linear regression. Household-level fixed-effects terms as well as the age fixed effects are included in all regressions. In addition, school-type variables (public/private) are included in the set of regressors in column (2) and the logarithmic education expenditure in column (3). All other covariates used in Table 4 are absorbed in the household-level fixed effects.

The lack of significance, however, can be attributed to the small size of the sample used in this analysis.

A related concern is that girls are likely to face a stiffer competition with siblings than boys because the former have more siblings than the latter on average. Therefore, our main results may be driven by the difference in the household competition between boys and girls. To address this concern, we also analyze a subsample of households in which there is only one child. This arguably mitigates the gender difference in the level of competition within the household. The results of this analysis are reported in Table 6. Because the sample size for this analysis is small, it is difficult to draw definitive conclusions. Still, columns (1)-(3) of this table indicate that the contradirectional gender gap remains albeit weaker.

We also alternatively use a subsample of children living in households with one boy and one girl in secondary-school age group and run linear regressions with household-level fixed effects as reported in columns (4)-(6). Unlike columns (1)-(3), we are able to control for the household-level observable

Table 6: Linear regressions by subsamples with different household compositions

	Only Child			**One-boy-one-girl**		
	d	Cond *y*	Cond *s*	*d*	Cond *y*	Cond *s*
Coef.	(1)	(2)	(3)	(4)	(5)	(6)
1995						
Girl	0.023	0.097	-0.056*	0.010	-0.139	0.001
	(0.052)	(0.151)	(0.032)	(0.033)	(0.096)	(0.041)
Obs	314	113	113	1,076	423	423
2000						
Girl	0.064	-0.130	-0.013	0.069**	-0.135	-0.044
	(0.052)	(0.142)	(0.038)	(0.032)	(0.091)	(0.029)
Obs	286	108	108	1,146	447	447
2005						
Girl	0.025	-0.129	-0.042	0.099***	-0.037	-0.022
	(0.048)	(0.095)	(0.028)	(0.032)	(0.077)	(0.017)
Obs	382	169	169	1,190	526	526
2010						
Girl	0.040	-0.089	-0.046**	0.093***	-0.068	-0.054**
	(0.038)	(0.076)	(0.018)	(0.035)	(0.070)	(0.022)
Obs	580	305	305	1,086	510	510
Basic covariates	Y	Y	Y	Y[a]	Y[a]	Y[a]
HH fixed effects	N	N	N	Y	Y	Y

[a]: The girl dummy and age fixed effects are included in columns (4)-(6). In addition, the school type dummy variables and logarithmic education expenditure are included, respectively, in columns (5) and (6). All other covariates are absorbed in the household-level fixed effects.

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at household levels are reported in parentheses. The estimations are obtained by equation-by-equation OLS estimations for each dependent variable. Only child subsample contains children from the households with only one child. One-boy-one-girl subsample contains children from the households with exactly two children, one secondary-school age boy and one secondary-school age girl.

and unobservable characteristics. Again, the statistical significance is weaker but broadly the signs are consistent with Table 4. Therefore, our results may be partly driven by intrahousehold competition, but it does not explain away all the contradirectional gender gap.

Another potential concern about Table 4 is the definition of the secondary-school age. Because of grade repetition and delayed entry into school, some secondary-school age children may be still in primary school and some post-secondary-school age children may be still in secondary school. To see if the presence of these children affects our results, we re-estimate the same model with an alternative definition of age groups where primary- and secondary-school age groups are defined as 6-11 and 12-17, respectively. The results are quantitatively and qualitatively similar.[16]

[16] Results are available upon request.

In addition, we also adopt some alternative specifications to better understand the contradirectional gender gap. First, the analysis of pooled sample with interaction terms between the girl dummy and time fixed effects indicates that the contradirectional gender gap did not change much over time (See Table 20 in Appendix F). We also conduct an analysis for urban and rural areas separately, because urban and rural areas are different in a variety of ways, including economic environment, labor market conditions, and societal attitudes towards female education. As detailed in Table 21 in Appendix F, the contradirectional gender gap is observed in both urban and rural areas and the gap in rural areas is generally larger in magnitude than that in urban areas.

Marginal Effects

Our regression coefficients from the three-part model do not provide readily interpretable quantities. Hence, we evaluate the marginal effect of being a girl at the sample mean, using the formula presented at the end of Section 3. The estimated marginal effects are presented in Table 7. Column (1) shows the presence of a significant profemale bias in the probability of enrollment except in 1995. For example, girls are 11.6 percentage points more likely to enroll in secondary schools than boys at the sample mean in 2010. The effects of being a girl on the total education expenditure and core expenditure conditional on enrollment are shown, respectively, in columns (3) and (5). Therefore, if we focus on school enrollees, girls enjoy less education expenditure and lower core share than boys.

For example, column (3) shows that the gender difference in the total education expenditure in 2005 was 416.6 BDT at the mean of the subsample of secondary school enrollees. Similarly, there exists a significant promale bias in the core component expenditure from 2000 onwards. However, as shown in column (2), when we consider the combined effect of enrollment and conditional expenditure, girls actually have a higher unconditional education expenditure than boys except for the year 1995. Further, the gender gap in the unconditional core expenditure is negligible as column (4) shows. These observations highlight the importance of clearly distinguishing the conditional and unconditional expectations.

The results above consistently show that girls received less expenditure in the core component than boys conditional on enrollment, and this gender gap grew over time. To identify the source of this growing gap, we computed the marginal effect of being a girl at the sample mean for the secondary school enrollees using the estimates from item-by-item Tobit regressions. The results of this analysis presented in Table 22 of Appendix F show that girls receive significantly less investment in tuition than boys for all the survey years. Girls also receive less in private tutoring, though the differences are not always significant. On the other hand, the only item for which girls somewhat consistently receive a higher amount is uniform, but this difference does not make up for the disadvantages in other

Table 7: Marginal effects of the girl dummy at the sample mean

Marginal effects at the sample mean	E(d) (1)	E(y) (2)	E($y\|d$ = 1) (3)	E(ys) (4)	E($ys\|d$ = 1) (5)
1995	-0.001	-40.5	-181.9***	-7.8	-110.5
	(0.016)	(26.3)	(67.7)	(16.3)	(92.7)
Obs.	5011	5011	1798	5011	1798
2000	0.126***	152.5***	-224.7***	11.5	-312.7***
	(0.014)	(29.8)	(76.3)	(24.6)	(62.5)
Obs.	4878	4878	1885	4878	1885
2005	0.114***	145.6***	-416.6***	-0.4	-367.3***
	(0.014)	(47.6)	(80.8)	(40.3)	(56.6)
Obs.	5638	5638	2579	5638	2579
2010	0.116***	313.0***	-616.8***	3.2	-604.9***
	(0.014)	(80.6)	(146.7)	(51.7)	(98.7)
Obs.	6205	6205	3172	6205	3172

Note: ***,**, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors in parentheses are obtained by simulation with 100 replications (see Appendix B for details).
E(·) stands for the expectation operator. Estimates in column (1) are the marginal effect of the girl dummy on the expected enrollment in secondary school for the children in the secondary-school age group. The marginal effects presented in Columns (2) to (5) are in BDT in nominal terms. Unconditional [Conditional] expectations are evaluated at the mean of the full sample [subsample of secondary school enrollees].

expenditure items. Therefore, girls have overall lower education expenditure and lower core expenditure conditional on enrollment and this female disadvantage mainly comes from tuition and private tutoring.

6 Analyzing the Role of FSPs

The contradirectional gender gap reported in the previous section is unique to Bangladesh and deserves further investigation. We conjecture that the FSPs may have played a role here for two reasons. First, the FSPs would encourage girls' school enrollment but may not necessarily affect the total education expenditure and core share conditional on enrollment. Second, India and Pakistan, which did not have a nationwide program similar to the FSPs, exhibit a clear codirectional promale bias.

We start with a brief background of the FSPs. Then, we provide supporting evidence for the relevance of the FSPs to the contradirectional gender gap in four different ways. First, we focus on the impact of the FSPs on the quantity measures of education by the double difference approach as this analysis provides relatively cleaner identification. Then, we incorporate in the three-part model the individual status of being an FSP recipient and the girl recipient ratio (GRR), which is defined as the number of the FSP recipients over the total number of girls of the same age in the division of residence and interpreted as a measure of the FSP intensity. Third, because the core share may be directly affected by the tuition waiver awarded to the FSP recipients, we mute its effect by either excluding the tuition from the analysis or imputing the tuition for FSP recipients. Finally, we analyze the gender gap in the educational outcome using the timely graduation from a secondary school as an outcome indicator.

Background of FSPs

The FSPs, which started as a small pilot program in 1982 and rolled out nationwide in 1994, consist of the following four projects: 1) the Female Secondary School Assistance Project, 2) the Female Secondary Stipend Project, 3) the Secondary Education Development Project, and 4) the Female Secondary Education Project. These projects are similar except that their funding agencies and the locations of operation differ. FSPs' target population is unmarried girls studying in secondary schools outside of the metropolitan areas that have signed a participation agreement. At the entry grades (grades 6 and 9), all female students in participating schools are eligible to benefit from the FSPs regardless of past attendance or performance. However, the following three conditions must be maintained for the continuation of the program: i) attending at least 75 percent of the school days, ii) achieving minimum marks of 45 percent in the annual school examination, and iii) staying unmarried until the SSC examination. The stipends are disbursed in two equal installments per academic year and the amount increases with the grade progression. The FSP recipients are also entitled to enjoy free tuition and schools are directly paid by the FSPs. However, around 15 percent of the FSP recipients, including both private- and public-school children, pay a small amount for tuition fee in our data. The FSPs' financial assistance is designed to cover slightly less than half of expenditure for secondary education.[17]

The nationwide rollout of FSPs took place rapidly between 1994 and 1995. According to BANBEIS (2006), the number of FSP recipients was only 70 thousand in 1994. The number jumped to 1.4 million in 1995 and more than doubled in the following two years. It continued to increase rapidly until reaching its peak of 4.2 million in 2002 after which it dropped to 2.3 million in 2005. These numbers are sizable both in absolute terms and relative to the cohort size (17.3 million in 2005) and the total enrollment (7.4 million in 2005) for the secondary-school age group.

However, with the intention of improving the quality of education and reaching out to the poor regardless of the gender, the FSPs were subsequently replaced by the Secondary Education Quality and

[17]The monthly stipend amount starts from 25 BDT for grade 6 and reaches 60 BDT for grade 10, The tuition fee paid under FSPs also increases from 10 BDT per month in grade 6 to 15 BDT per month in grade 10 for public schools, and the amount is higher for private schools by 5 BDT per month. In addition, the book allowance and examination fee are given to the grades 9 and 10 recipients, respectively. See also Table 2 of Bangladesh Ministry of Education (1996) for further details of the FSPs.

Access Enhancement Program (SEQAEP) in 2008, which targeted the poor in remote subdistricts in Bangladesh. Thus, the FSPs are relevant only to the early three rounds of our analysis, namely 1995, 2000, and 2005, whereas the SEQAEP was in place by 2010.

Because of the lack of clarity in the way the resources for the FSPs were allocated and because of the lack of information on the individual FSP eligibility in our dataset, our analysis is necessarily based on the actual receipt of the program. Along with this problem, it is also difficult to obtain a clean identification of the impacts of the FSPs for two additional reasons. First, the assignment of FSPs is nonrandom as there are some eligibility criteria. Second, we have limited data before the national rollout of the FSPs. In particular, the individual-level information on education expenditure is only available from the year 1995 when the FSPs were already available nationwide. Therefore, we start the analysis of the FSPs with quantity measures of education to enable a (relatively) clean identification through a double difference approach.

Impact of the FSPs on the Quantity of Education

In this subsection, we focus on the impact of the FSPs on two quantity measures of education. The first quantity measure of education is the completed years of education (YrEdu_{ih}) for each working-age individual i between 19 and 65 years of age in each household h for each HIES survey round. The second analysis of a quantity measure of education is based on the retrospective panel data on enrollment (Enroll_{iht}) for each child i in household h in calendar year t. The retrospective panel data is created under the assumptions that each child enters secondary school (grade 6) at the stipulated secondary-school entry age of age 11 and that no child repeats a grade.[18] Then, we go back the calendar year to determine whether the child was in school. As an example, consider a boy who is 17 years old in 2005. If he completed grade 8, the last age at which he was in school would be 13. Therefore, he was in a secondary school between 1999 and 2001 (ages 11-13) and out of school between 2002 and 2005 (ages 14-17). We do this for all individuals born in or after 1949 in each round of HIES survey up to 2007, and focus on the records that correspond to the secondary-school ages of 11-15, such that the calendar year for the analysis starts from 1960(=1949+11).[19]

We estimate the impacts of the FSPs on these quantity measures by double difference regressions, where one difference is taken between the two genders and the other between those who are covered and not covered by the FSPs. Specifically, we obtain from Table 3 of Shamsuddin(2015, p. 432) the year in which each subdistrict was covered by an FSP and use it to determine the FSP coverage (FSPCover),

[18] According to BANBEIS(1995,2010), the repetition rate was around 5 percent and 4 percent in years 1995 and 2010, respectively.
Thus, our nonrepetition assumption serves as a reasonable approximation.

[19] We followed Heath and Mobarak(2015) to determine the starting year of our study period. The results remain similar even when we shift the starting year to 1980.

or whether an individual is in a subdistrict covered by an FSP in the reference year. Here, the reference year is year *t* [the calendar year in which the child is at age 11] for the regression of Enroll [YrEdu]. The construction of FSPCover is based on the assumption that the location of individuals does not change over time and this is a reasonable approximation, because the migration rate is low, especially early years, in Bangladesh. Since the rollout of the FSPs is plausibly exogenous and all unobservable time-invariant household effects are controlled for, the double difference approach substantially reduces the endogeneity concerns.

To be specific, the following double difference specifications are used:

$$YrEdu_{ih} = \alpha_1 Girl_{ih} + \alpha_2 FSPCover_{ih} + \alpha_3 Girl_{ih} \times FSPCover_{ih} + \sum_b \mu_b \times \mathbf{1}(Birth\ year_{ih} = b) + \theta_h + \varepsilon_{ih}, \quad (5)$$

and

$$Enroll_{iht} = \alpha_1 Girl_{ih} + \alpha_2 FSPCover_{iht} + \alpha_3 Girl_{ih} \times FSPCover_{iht} + \sum_{a=11}^{15} \beta_a \times \mathbf{1}(Age_{iht} = a) + \sum_b \mu_b \times \mathbf{1}(Birth\ year_{ih} = b) + \lambda_t + \theta_h + \varepsilon_{iht}, \quad (6)$$

where μ_b , β_a, λ_t, and θ_h represent, respectively, birth year-, age-, time-, and household-specific fixed effects. ε is the idiosyncratic error term.

Table 8 shows the OLS regression results of the two equations above. Panel A reports the regressions of the FSP coverage on the completed years of education for working-age individuals for each survey round, where the mean of the dependent variable for a given round is reported in the last row. Because the overwhelming majority (99.7 percent) of the working age adults in 1995 were not covered by the FSPs, it is not surprising that the impact of the FSPs on the years of completed education is insignificant (columns (1)). In the later rounds when the FSPs started to rapidly roll out nationwide, the years of schooling increased significantly for girls who were eligible for the FSPs at age 11. Column (4) shows that the promale gender gap in the years of education narrowed by 1.88 years after the FSPs rolled out in 2010.

Panel B presents the regression of the enrollment status for the secondary school children aged between 11 and 15. The first row indicates that the girls are *less* likely to be in secondary school than boys by 15-18 percentage points across years, but the FSPs had a significantly positive impact and indeed more than offset this negative effect of being a girl after 2000 as the third row shows. For example, column (4) shows that the positive impact of the FSPs on enrollment was 19.1 percentage

Table 8: Impacts of the FSPs on the quantity measures of education

	HES 1995	**HIES 2000**	**HIES 2005**	**HIES 2010**
Coef.	(1)	(2)	(3)	(4)
	Panel A: Years of education			
Girl	-1.977***	-1.863***	-1.943***	-2.000***
	(0.041)	(0.040)	(0.038)	(0.042)
FSPCover	0.667	-1.714***	-0.245	-0.358
	(0.807)	(0.368)	(0.481)	(0.562)
Girl × FSPCover	-0.390	1.661***	1.775***	1.876***
	(1.123)	(0.179)	(0.104)	(0.084)
Obs	18,303	18,828	24,912	29,519
Mean of dep. var.	3.460	3.607	4.193	4.410
	Panel B: Enrollment using retrospective data			
Girl	-0.148***	-0.164***	-0.172***	-0.176***
	(0.004)	(0.004)	(0.004)	(0.004)
FSPCover	-0.049	-0.175***	-0.065	-0.045
	(0.044)	(0.043)	(0.049)	(0.054)
Girl × FSPCover	0.131***	0.175***	0.188***	0.191***
	(0.012)	(0.009)	(0.007)	(0.007)
Obs	102,319	110,469	150,518	162,056
Mean of dep. var.	0.265	0.279	0.319	0.335

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. In Panel A, we additionally include the fixed-effects terms specific to the birth year and household. In Panel B, we additionally include the fixed-effects terms specific to the birth year, age at the time of observation, household, and year of observation.

points, reversing a promale gap of 17.1 percentage points to a significant profemale gap of 1.5(=19.1-17.6) percentage points with a *t*-statistic of 7.2. These figures are both statistically and economically significant.

The double difference specification significantly reduces the endogeneity concerns, because it is immune to selection on time-invariant household characteristics. However, one might argue that the rollout of the FSPs is not random. That is, the government and donors may have chosen to start the program in places where the promale gender bias is most prevalent. Nevertheless, the contamination from the selection of program areas is unlikely to be serious, because the coverage of FSPs was highly limited before 1994[20] and it expanded rapidly in 1994. Put differently, our identification is primarily through the interaction between the girl dummy and cohorts born after 1983(=1994-11) and not through the differences in timing in the implementation of the FSPs across subdistricts. Further, we have conducted a falsification test to boost the credibility of the discussion above. In this test, we focus on

[20]For example, among the working adults aged between 19 to 65 years in 2010, only 2 percent of the FSP coverage come from the pre-1994 period.

the period in which FSPs were not introduced and re-estimate the impact of FSPs by hypothetically shifting the introduction of the FSPs in each subdistrict earlier by five years (thus, for a majority of subdistricts, we pretend that the FSP coverage started in 1989 instead of in 1994). As expected, the impact of FSP coverage in the falsification test was found to be small in absolute value and statistically insignificant, as detailed in Appendix D.

It should also be noted that our finding of the positive impact of the FSPs on enrollment is in line with existing studies (Khandker et al.,2003; Schurmann,2009; Asadullah and Chaudhury,2009; Shamsuddin,2015). However, it is notably at odds with Heath and Mobarak (2015, hereafter HM), who found no evidence that the FSPs have a positive impact on female enrollment. Instead, they found that what led to an improvement in female secondary education—in their study areas—was an increasing demand for female labor.

Their analysis is based on a triple difference approach, where the primary school children are used as a comparison group in addition to the two differences (i.e., difference between the two genders and the difference between before and after the coverage by the FSPs) we take in our double difference estimation discussed above. Thus, to understand the source of the difference from HM clearly, we also conducted a triple difference analysis. We first replicated their results and progressively changed some elements of their analysis, including the data, the subdistricts studied, and the definitions of the FSP coverage and eligibility criterion. This exercise, detailed in Appendix E, shows that the HM's findings seem to be driven by a combination of the particular data they used, geographic coverage of their data, and the FSP eligibility criterion used in their study. In particular, their FSP eligibility criterion of at least 6 years of schooling appears to have led to an underestimation of the FSPs' impact on enrollment. This is because those girls who have completed a primary school are eligible for the FSPs if they go to a secondary school, such that girls who are in grade 6 (and thus not yet completed 6 years of schooling) are already able to benefit from the FSPs. Our preferred estimate of the FSPs' impact on enrollment within the framework of the triple difference estimation, which uses the nationally representative HIES data and the completion of primary school as the eligibility criterion for the FSPs, shows that the FSPs' impact on enrollment is positive and statistically significant.

Incorporating the FSPs in the three-part model

To have a more comprehensive understanding of the FSPs impact on education expenditure, we now incorporate the FSPs in the three-part model using the HIES data for the years 2000 and 2005 as they contain information on the individual status of the receipt of FSPs.[21] This is important, because

[21]HES 1995 does not contain the information on the FSP status. HIES 2010 was also not used because the FSPs were already terminated by then. It should also be noted that the HIES 2000 dataset appears to underrepresent the

Table 9: Three-part model estimation with the FSP status

Year	*Coef.*	*d*	Cond *y*	Cond *s*	*d*	Cond *y*	Cond *s*
		(1)	(2)	(3)	(4)	(5)	(6)
2000	Girl	0.339***	-0.245***	-0.062***	0.228**	-0.236***	-0.018
		(0.039)	(0.054)	(0.019)	(0.091)	(0.085)	(0.028)
	FSP		0.123**	-0.034**		0.149***	-0.037**
			(0.049)	(0.015)		(0.051)	(0.017)
	GRR				0.769**	-1.299***	0.247**
					(0.346)	(0.297)	(0.121)
	Girl × GRR				0.378	-0.100	-0.138*
					(0.286)	(0.260)	(0.078)
	Obs.		4878			4878	
2005	Girl	0.289***	-0.178***	-0.058***	0.110	-0.107	-0.007
		(0.034)	(0.034)	(0.014)	(0.093)	(0.072)	(0.025)
	FSP		0.046	-0.026***		0.075**	-0.025***
			(0.036)	(0.009)		(0.036)	(0.010)
	GRR				0.470	-1.004***	0.020
					(0.306)	(0.227)	(0.093)
	Girl × GRR				0.656**	-0.308	-0.184**
					(0.315)	(0.233)	(0.081)
	Obs.		5638			5638	

Note: ***,**, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. Girl recipient ratio (GRR) is the ratio of girl recipients to all girls for a given age group in a given division. The covariates discussed in Table 4 are also included in all regressions.

the education expenditure of the FSP recipients is affected by the tuition waiver and stipend provided by the FSPs. Thus, we include the dummy variable for the FSP recipients, who are all girls, in the conditional expenditure and core share equations.

The regression results are reported in columns (1)-(3) of Table 9. As the comparison with Table 4 shows, the inclusion of the FSP dummy makes the coefficients on the girl dummy in the conditional expenditure and core share equations even more negative. The point estimates on the FSP dummy are positive in the conditional expenditure equation, while they are significantly negative in the core share equation for both years.

To understand where this impact is coming from, we report in Table 23 in Appendix F the marginal effects using item-by-item Tobit regressions that include both the girl and FSP-recipient dummy variables. This analysis shows that the FSP recipients spend less on tuition as expected, because the tuition is waived for the FSP recipients. The FSP recipients receive more expenditure on private tutoring and materials than non-recipients, but this positive effect of the FSPs does not offset the negative effect of

FSP recipients. Based on BANBEIS(2006), the ratio of the number of FSP recipients to the number of female enrolled secondary school students is 86 percent, while the figure directly derived from the HIES 2000 data is 59 percent. Therefore, the interpretation of the results for the year 2000 requires some caution. This issue does not exist for the year 2005.

being a girl. Thus, the recipients of the FSPs still do not enjoy as much core education expenditure as boys. For the peripheral items, FSP recipients get a higher expenditure in most items, especially in uniform, meals, and transportation, with a notable exception of admission. Overall, this analysis indicates that the FSPs did not increase the core expenditure among school enrollees.

Next, we study the spillover effect of FSPs by exploiting the variations across regions and ages in the intensity of FSPs as measured by the GRR. In columns (4)-(6) of Table 9, we report the results of the three-part model estimation that includes as covariates the GRR and its interaction with the girl dummy in addition to all the covariates used in columns (1)-(3) of the same table. These results show that girls living in more FSP-intensive divisions (for their age) are more likely to be enrolled in school. This indicates that FSPs may have a positive spillover effect on families living in the same area such that parents are more likely to enroll their children, particularly daughters, in school. However, there is no evidence that FSPs facilitate parental investment in the quality of education for girls. The coefficient on the interaction terms in the conditional education expenditure is negative for both 2000 and 2005, and the same coefficient in the conditional core share equation is significantly negative in both years.

We also investigate the spillover effect of FSPs on boys' education expenditure. Due to the non-random assignment of FSPs and the limited data of pre-FSPs period, clean identification is difficult. Nevertheless, we provide some supporting evidence of the spillover impact of the FSPs by comparing education expenditure of boys from households with and without a FSP recipient. We estimate the three-part model with a subsample of boys. As the results reported in Table 10 show, boys from a FSP-receiving household (FSP HH), or a household with at least one FSP recipient, are more likely to enroll in school than boys from a household without a FSP recipient. However, conditional on enrollment, they receive less education expenditure than boys from non-FSP households, though there is no significant difference in core share. This indicates that there is positive spillover effects on boys' enrollment status, even though we cannot exclude the possibility that this is driven by the unobserved heterogeneity between FSP-receiving and non FSP-receiving households. On the other hand, the negative spillover effects of the FSPs on boys' education expenditure conditional on enrollment suggest that households with FSP recipients may shift education expenditure from boys to girls. Thus, between the income effect of the FSPs through stipend and the substitution effect due to the lower relative price of girls' education, the former appears to dominate the latter, even though such an interpretation requires caution due to the nonrandom assignment of the FSPs.

Table 10: Three-part model estimation with a subsample of boys

	HIES2000			HIES2005		
	d	cond *y*	cond *s*	*d*	cond *y*	cond *s*
Coef.	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: All boys					
FSP HH	0.138	-0.215**	-0.000	0.300***	-0.156**	-0.054*
	(0.101)	(0.087)	(0.028)	(0.104)	(0.067)	(0.029)
Obs		2,488			2,848	
	Panel B: Boys in one-boy-one girl households					
FSP HH	0.264*	-0.200*	0.054	0.416***	-0.192*	-0.049
	(0.159)	(0.114)	(0.067)	(0.133)	(0.114)	(0.039)
Obs		573			595	

Note: ***,**, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. The estimates are obtained using the three-part model constructed in Section 3. The covariates discussed in Table 4 are also included in all regressions.

Muting the FSPs Tuition Waiver

As mentioned above, the tuition waiver is an important component of the FSPs. The tuition waiver encourages enrollment but also tends to negatively affect the conditional expenditure and core share among the school enrollees. However, the latter negative effects may be spurious. This may be simply because the FSPs are replacing the household's tuition expenditure for girls through the tuition waiver; the FSPs might not have any impact on the conditional expenditure and core share once the tuition waiver is taken into consideration.

To see if this is a possible explanation, we attempt to mute the impact of the tuition waiver through two alternative empirical exercises: exclusion and imputation. In the exclusion exercise, we exclude the tuition fee from the calculations of both the total education expenditure and core expenditure. In the imputation exercise, we impute the tuition fee for the FSP recipients using a linear prediction model. Then, the imputed tuition fee is computed by predicting the fee with the estimated parameter values but omitting the term involving the FSP-recipient dummy. This predicted amount, which is truncated from below at zero, can be interpreted as the tuition fee parents would have to spend had their daughter not received a tuition waiver.

The results of these two exercises are presented in Table 11 together with the baseline estimates taken from Table 4 for the ease of comparison. As the table shows, the absolute value of the coefficient on the girl dummy becomes smaller than the baseline results in each of the three equations after turning off the impact of tuition waiver either by exclusion or imputation. This indicates that our finding is indeed driven in part by the spurious effect coming from the tuition waiver. However, as Table 11 shows, the sign and statistical significance of the coefficient on the girl dummy remain the same. Therefore,

Table 11: Three-part model estimation with the impact of the tuition waiver muted

Year	Model	*d*	Cond *y*	Cond *s*
	Baseline	0.339***	-0.174***	-0.082***
		(0.039)	(0.049)	(0.014)
2000	Exclusion	0.322***	-0.081*	-0.062***
		(0.039)	(0.045)	(0.013)
	Imputation	0.324***	-0.072	-0.055***
		(0.039)	(0.047)	(0.011)
	Baseline	0.291***	-0.154***	-0.071***
		(0.034)	(0.027)	(0.012)
2005	Exclusion	0.274***	-0.079***	-0.058***
		(0.035)	(0.028)	(0.011)
	Imputation	0.279***	-0.106***	-0.050***
		(0.035)	(0.028)	(0.010)

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. Additional covariates discussed in Table 4 are also included. The baseline results are taken from Table 4. In the exclusion exercise, tuition fee is excluded from both total education expenditure and core expenditures to compute *s*. In the imputation exercise, we instead impute the tuition fee for FSP recipients using the predicted value from a linear mode estimated with the pooled sample that include the fixed-effects terms for the following categorical variables: enrollment status, FSP-recipient status, district of residence, survey year, gender, and school type (private/public).

the earlier finding of the contradirectional gender gap still remains valid even after muting the effects of tuition waiver.

Since Table 11 does not distinguish girls by the FSP-recipient status, we also consider a model that incorporates the FSP status in the three-part model and mute the effects of tuition waiver. In the top panel of Table 12, we present the baseline estimation of the three-part model with the FSP status reported in Table 9. Then, as with Table 11, we mute the effects of tuition wavier by either exclusion or imputation.

As Table 12 shows, FSP girls enjoy a higher total education expenditure than non-FSP girls even in the baseline results, and the difference becomes more significant, both economically and statistically, once the effects of tuition waiver are muted. By comparing the signs and sizes of the coefficients on FSP and Girl, it can also be seen that the positive impacts of the FSPs can substantially mitigate the promale bias in the total education expenditure (conditional on enrollment). Nevertheless, there is no significant difference in the core share by the FSP status and girls receive significantly lower core share than boys. Taken together, FSPs did not appear to remove the gender gap in the education expenditure on the core component conditional on enrollment.

Table 12: Three-part model estimation with FSP status after muting the tuition waiver

	HIES2000			HIES2005		
	d	cond *y*	cond *s*	*d*	cond *y*	cond *s*
Baseline						
Girl	0.339***	-0.245***	-0.062***	0.289***	-0.178***	-0.058***
	(0.039)	(0.054)	(0.019)	(0.034)	(0.034)	(0.014)
FSP		0.123**	-0.034**		0.046	-0.026***
		(0.049)	(0.015)		(0.036)	(0.009)
Exclusion						
Girl	0.323***	-0.191***	-0.052***	0.273***	-0.128***	-0.050***
	(0.039)	(0.053)	(0.018)	(0.035)	(0.035)	(0.013)
FSP		0.192***	-0.018		0.097***	-0.016
		(0.050)	(0.018)		(0.036)	(0.011)
Imputation						
Girl	0.327***	-0.228***	-0.055***	0.281***	-0.178***	-0.051***
	(0.039)	(0.053)	(0.017)	(0.035)	(0.034)	(0.013)
FSP		0.288***	0.002		0.147***	0.002
		(0.047)	(0.019)		(0.036)	(0.011)

Note: ***,**, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. The estimations are obtained using the three-part model constructed in Section 3. In all regressions, the following covariates are also included: logarithmic per capita expenditure, logarithmic household size, father's and mother's education in years, number of children, female head, wage-worker head, head's age, and religion (muslim/hindu), urban area, and dummy variables for the child's age. In addition, the school accessibility variables, school-types dummy variables (private/public), and logarithmic education expenditure are also included in the equations for x_d, x_y, and x_s, respectively. Baseline results are taken from Table 9. See the tables note for Table 11for the details of the exclusion and imputation exercises.

Impact on Timely Secondary School Graduation

The results of the previous subsections suggest that the FSPs promoted the girls' enrollment in secondary schools but fell short of reducing the gender gap in the investment in the quality of education. Indeed, the FSPs have been criticized for the lack of attention to the quality of education (Mahmud, 2003; Raynor and Wesson, 2006). Our analysis highlights the reason why the quality of education for girls lag behind that for boys among the school enrollees from the perspective of complementary investment in education from households.

Nevertheless, it is not evident from the preceding analysis how this has affected the performance of girls in school relative to boys. Unfortunately, our data do not contain standard performance measures of education such as test scores. Therefore, we use completion of secondary school (roughly) on time as an indicator of education performance. This is a reasonable indicator because passing the SSC examination requires a certain level of mastery of the secondary-level curriculum.[22] Based on our age group classification, a child is regarded to have completed secondary school (roughly) on time if he/she has already passed at least grade 10 (SSC or equivalent) when he/she is in age range16-20. For this exercise,

[22]To complete secondary education, the child has to pass the SSC exam. As shown in Figure 1, the passing rate varies and may be as low as 40 percent depending on the year. Thus, passing the SSC examination is not trivial.

Table 13: OLS regressions of on-time secondary school completion by year

Sec complete on time *Coef.*	**1991** (1)	**1995** (2)	**2000** (3)	**2005** (4)	**2010** (5)	**2005** (6)	**2010** (7)
				Panel A: All individuals aged 16-20			
Girl	-0.043***	-0.053***	-0.043***	-0.014	-0.005	0.004	0.065**
	(0.012)	(0.012)	(0.012)	(0.010)	(0.011)	(0.020)	(0.027)
Lagged GRR						0.242***	0.699***
						(0.091)	(0.091)
Girl×Lagged GRR						-0.064	-0.261***
						(0.070)	(0.094)
Obs	3,043	3,752	3,988	5,055	5,316	5,055	5,316
				Panel B: All primary graduates aged 16-20			
Girl	-0.019	-0.081***	-0.063***	-0.022*	-0.024*	0.032	0.088***
	(0.027)	(0.019)	(0.017)	(0.013)	(0.014)	(0.027)	(0.033)
Lagged GRR						0.345***	0.835***
						(0.122)	(0.115)
Girl×Lagged GRR						-0.201**	-0.425***
						(0.094)	(0.116)
Obs	1,223	2,113	2,621	3,716	4,089	3,716	4,089

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at household level are reported in parentheses. The dependent variable is a dummy variable for the completion of secondary school on time, which takes one if an individual aged between 16 and 20 at the time of survey had already completed grade 10 or higher. Lagged GRR is the GRR at division-age level five years before the survey. In 2005 [2010], we use GRR for the year 2000 [2005]. In all regressions, the following covariates are also included: logarithmic expenditure per capita, logarithmic household size, the dummy variables for the household heads' education level (primary, secondary and higher), female head, wage-worker head, head's age and religion (muslim/hindu), urban area, and dummy variables for the child's age. Panel A uses a sample of all individuals aged between 16 and 20 and Panel B uses a subsample of primary graduates among them.

we additionally use HES 1991 dataset as it contains information necessary to construct the indicator for completion on time.

In columns (1)-(5) of Panel A of Table 13, we report the estimated effects of being a girl on timely completion of secondary school for each survey year through OLS regressions. The effects have become less promale and the beginning of the narrowing of the gap roughly corresponds to the onset of the FSPs, which seems to indicate that FSPs helped close the gender gap in timely completion of secondary education.

However, if we restrict the sample to those who have already completed primary education, the picture looks different as the columns (1)-(5) in Panel B of Table 13 show. The gender gap in the timely completion of secondary education conditional on the completion of primary education is larger than that in the unconditional sample—except for the year 1991 when the FSPs were yet to be rolled out nationwide. This indicates that the narrowing of gender gap observed in Panel A may be due to the improvement in girls' secondary enrollment. That is, if more girls are enrolled, they have a higher unconditional probability of completion. However, the results of panel B indicate that the school performance of girls among the potential school enrollees, or those who have completed primary school, was worse than that of boys. Assuming that the gender gap in the quality of education translates into the gender gap in school performance, the result above are consistent with our finding above that the quality of education for girls conditional on enrollment consistently lagged behind that for boys.

Next, we attempt to understand the impact of the FSPs on the timely graduation from secondary school. This is challenging, because we do not have the history of the FSP-recipient status in the past. Instead, we include in the regressions the lagged FSP intensity—as measured by GRR five years prior to the survey—and its interaction with the girl dummy. That is, we use the GRR for the year 2000 [2005] and its interaction term in the analysis of timely graduation in the year 2005 [2010]. The lagged variable would arguably reflect the cumulative impact of the FSPs in the last five years. Note, however, that the results for the year 2010 suffer from the contamination of the sample because some of the individuals in the sample may have benefitted from the SEQAEP.

The results of this analysis are presented in columns (6)-(7) of Table 13. For all children aged between 16 and 20, girls living in more FSP-intensive areas are less likely to graduate on time than boys as the negative point estimates on the interaction term (i.e., Girl $\times$ Lagged GRR) indicate. When we look only at the subsample of those who have completed primary education, the promale gender gap is significant in more FSPs intensive areas. Thus, consistent with our earlier findings, there is no evidence that the FSPs improved the quality of education for secondary school girls relative to boys. If anything, the girls in high FSP-intensive areas are less likely to graduate from secondary school on time than the girls in low FSP-intensive areas, indicating the impact of the FSPs on the performance in secondary school was possibly negative.

In sum, these preceding analyses collectively indicate two points. First, the FSPs increased the female secondary school enrollment and years of education. Second, despite the increase in these quantity measures of education, the FSPs did not attract complementary investment in the quality of education from the households. As a result, the quality and performance of education for girls appears to have lagged behind those for boys among school enrollees.

7 Diagrammatic Analysis and Labor Market Returns

While the girls' secondary school enrollment rate has substantially increased over the last decades both in terms of the absolute level and relative to the boys' in Bangladesh, the findings so far demonstrate that girls lagged behind boys in the performance of education likely because of the lack of complementary spending from households in the quality of education. Therefore, even though the FSPs have been successful in eliminating the gender gap in enrollment, they did not remove the gap in education quality once girls are in school. In this section, we offer a simple demand-supply diagram for the market of education quality for the secondary school children to explain why the FSPs do not necessarily change the promale gender gap in the expenditure on the quality of education. We then explore the relevance of gender difference in the labor market returns to our findings.

We start with a simple demand and supply diagram for the market of education quality in Figure 3. While we abstract away from the details about what constitutes education quality in this analysis, it can be considered as private tutoring for the ease of understanding. The black solid line in the figure represents the supply of the education quality. The demand curves for girls and boys are shown in solid red and blue lines, respectively. In this figure, the demand for girls is always lower than that for boys, representing promale bias in the market for education quality. The aggregate demand is the kinked line in purple.

The diagram is somewhat similar to Dang and Rogers (2015), who include private tutoring into the analysis of education in Vietnam. However, our diagram is distinct in two important aspects. First, the decision to enroll is a trivial decision in Vietnam as most children go to school and thus enrollment decision is not separately considered,[23] whereas secondary school enrollment remains an important household decision in Bangladesh. Second, we also explicitly distinguish between boys and girls and use the diagram to analyze the impact of the FSPs.

In Figure 3, the equilibrium price is given by (the length of) OA and equilibrium demand for the boys and girls are AB and BC, respectively. In the standard framework of economic analysis, the FSPs would be expected to reduce the cost of sending children to school, which may in turn lead to an increase in the complementary demand for the education quality, shifting the demand curve for the girls to the dashed red line. Then, the lower part of the aggregate demand curve will also shift to the dashed purple line. In this case, the demand for the quality of education by girls will increase to DE, whereas that by boys will decrease to EF. The demand for the education quality for boys decreases because of the higher equilibrium price resulting from higher competing demands from girls. Hence, in

[23]Dang and Rogers (2015) report that 87 percent of children aged between 6 and 18 were enrolled in a school in the past 12 months in 2006.

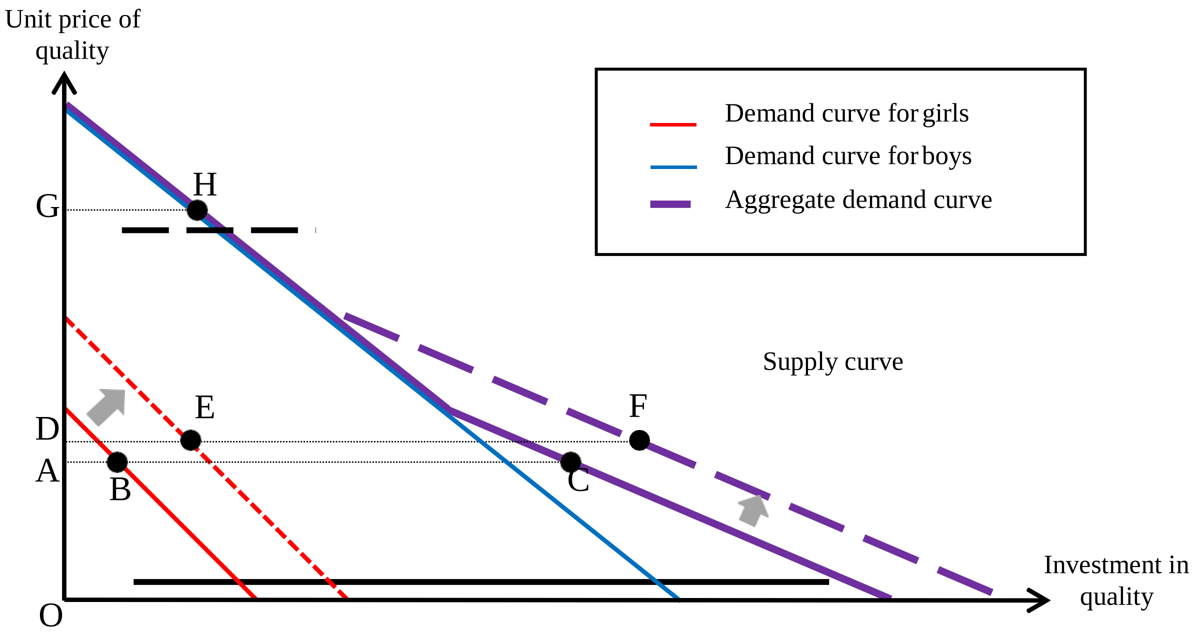

Figure 3: Demand and supply for the investment in the quality of education

this picture, the aggregate investment in the education quality for girls would increase relative to that for boys as a result of the FSPs. Arguably, this would be the outcome that is naturally expected from the introduction of the FSPs.

However, our earlier empirical findings are clearly inconsistent with increased complementary demand for education quality. Figure 3 also allows us to explain why the expected outcome may not occur. First, the demand for the quality of education may remain unchanged if the equilibrium price is above the choke price for girls. To demonstrate this point, suppose now that the supply curve is the black dashed line such that the equilibrium price is GH regardless of the presence of the FSPs. In this case, the equilibrium demand from boys is GH and that from girls is zero, whether or not the FSPs are in place. Second, it is also possible that the households at the margin who send girls to a secondary school because of the FSPs may be unwilling to invest in the education quality. In this case, the demand curve for girls would be still the red solid line such that the FSPs would bring about no change in the market of education quality.

These possibilities are also consistent with our observation from Table 4 that the pattern of gender bias in 1995 is different from other years. Because the FSP coverage was substantially lower in 1995 than in 2000 and 2005, it is not surprising that the gender gap in enrollment was insignificant in 1995. Furthermore, because many of the compliers—the girls who would go to school if they receive the FSPs but would not go otherwise—are probably not covered by the FSPs in 1995, the FSPs' effect on the core share is also small. While we do not have definitive evidence, this possibility is consistent with both the empirical results and diagrammatic analysis presented above.

The discussion above does not show, however, why the choke price for the education quality is so low for girls or why the compliers may not want to make an investment in the education quality for girls. One possible answer would be an inherent gender bias in the parental decision-making. However, one may also consider the labor market returns. As Asadullah (2006) argues, if education of girls is deemed to bring about no returns to their parents or to lower the prospect of marriage, parents may be discouraged from investing in girls. This argument is true even when parents have no inherent gender bias. Hence, even if parents do not have an inherent gender bias as the experiment by Begum et al. (2018) suggests, they may still choose not to invest in the quality of education for girls simply because it is not a good investment.

There are at least two reasons to believe that the labor market returns are relevant. First, the return on the investment in the quality of education for girls may be lower than that for boys, simply because a higher fraction of women than men do not work after leaving school. Indeed, the female labor force participation rate for individuals aged 15 and above was only 36 percent in 2010. This denotes a significant increase from 16 percent in 1995, but it remains substantially lower than the corresponding figure for males, which has been stable at around 85 percent (Rahman and Islam, 2013). Even if women work, they tend not to work full-time, which in turn means that the return on the investment in the quality of education would be lower, everything else being equal. Even though the average number of hours worked per week by employed female labor force increased from 26 in 2006 to 35 in 2010, it remained much lower than the corresponding figure for male labor force, which was slightly above 50 during the same period (Rahman and Islam, 2013).

Second, it may also be the case that women's quality of education may not be valued as much as men's counterpart in the labor market. If that is the case and if the distribution of the quality of education is the same between men and women, the female wage dispersion would be lower than male wage dispersion. To see if this may be the case, we use a subsample of wage earners aged between 19 and 65 in the HIES 2000, 2005, and 2010[24] to create a box plot of their hourly wage rates by education level and gender among adults for each survey year (Figures 4 (a)-(c)). As the plot shows, the hourly wage rates for the female workers tend to be lower and less variable than those for male workers across all education levels and in all years. Thus, our results are consistent with the possibility that the quality of education for women may not be as important as that for men in the labor market.

There is, however, an alternative possibility: the gender difference in the wage dispersion may be driven by the gender differences in the dispersion in the quality of education. However, we argue that this possibility is unlikely to be very important. Because private tutoring was very rare for

[24]HES 1995 does not contain individual wage data.

Figure 4: Box plot of hourly wage by education level and gender using HIES wage earners subsample. Wage data are all converted to hourly wage.

older generations, the gender difference in the dispersion of the quality of education is also likely to be smaller for them. Based on this observation, we also created a box plot with a sample of workers aged 30 years or above in the HIES 2000 data. As Figure 4 (d) shows, the wage dispersion for males is much larger than that for females, even for the generation for which private tutoring was rare. Hence, we favor the interpretation that the returns to the quality of education for males is larger than those for females.

8 Discussion

Gender parity in enrollment is a big achievement, but we would be merely indulging in illusions if we equate it to gender parity in education. The contradirectional gender bias in Bangladesh documented in this study—profemale bias in enrollment and promale bias in the total education expenditure and the core share in the total education expenditure among school enrollees—clearly illustrates that gender parity in education cannot be measured by the gender parity in enrollment alone.

At a first glance, the contradirectional gender gap is puzzling, because it cannot be explained by gender discrimination and because it is not found anywhere else, including India and Pakistan. Our analysis, however, indicates that it is driven at least in part by the presence of the FSPs. Using a double difference strategy, we show FSPs helped to bring girls to school. However, the analysis of the three-part model suggests that the FSPs did not attract sufficient complementary investment from households in the quality of education, which in turn appears to have resulted in the underperformance of girls relative to boys among the primary school graduates. We further explored the possible explanations for the lack of investment in the quality of education from the households and provided some indicative evidence that the expected labor market returns on the investment in the quality of education for girls may have been lower than those for boys.

Because of the data limitations, at least four potentially important factors were not taken into account in this paper. First, it is possible that the FSPs *directly* lower the quality of education for girls by selectively attracting girls to schools and putting them in crowded classrooms. The teacher-student ratio (TSR) in secondary schools was only 1:24 in 1990 but rose by 50 percent to 1:36 in 2010, indicating that the classrooms have become overcrowded. Moreover, given the crowded classrooms, many school teachers capitalized on this opportunity by systematically exerting less effort in school teaching and promoting private tutoring to earn extra income (Shahjamal, 2000; Mahmud, 2003).

Second, there may be a gender difference in the effective price of private tutoring, particularly if parents need to pay additional supporting costs, such as private transportation for an accompanying guardian. Indeed, it is estimated that the cost of private tutoring for girls is 13 percent more expensive than that for boys (CAMPE, 2006, Table A4.1 in p. 120). This observation is important, because the first-generation learners typically get no help with their study outside the classrooms. This, in turn, makes it difficult for children from disadvantaged backgrounds—particularly girls—to pass the SSC examination, because after-school tutoring is crucial for students struggling academically, especially in mathematics and English (Nakata et al., 2018).

Third, a related factor is the supply-side constraint on female private tutors. While we are not aware of data on the availability of tutors, it seems likely that female private tutors were scarce, particularly in earlier years. Therefore, some parents with traditional social norms may choose not to hire a private tutor for their daughter, not because they are unwilling or unable to pay, but because there is no female tutor available. However, the supply-side constraint is unlikely to be of primary importance, because the contradirectionality of the gender gap did not change much after the year 2000, even though women have been getting better educated.[25]

Fourth, the argument we put forth in Section 7 is based on an implicit assumption that the households have the information and rationality to make education decisions based on the labor market returns. This, of course, may not be true. For example, the gender gap in the total education expenditure and core share may be attributed to lack of knowledge, misinformed beliefs, incorrect valuation

[25]According to BANBEIS (2010, Table 2.1.0 in p. 30), the proportion of female teachers in secondary schools was 13.88 percent in 1995. This figure has reached 23.09 percent in 2010.

of schooling returns, and gender difference in the way future costs and benefits are discounted (Baland and Robinson, 2000). Even if parents do not have inherent gender bias, their decisions may be biased if doing otherwise is socially costly in the presence of strong patriarchal social norms. Given these possibilities, labor market returns are likely to be only one of—and not the only—potential factors that lead to the gender gap in the investment in the quality of education from households.

Our results highlight both the opportunities and challenges that a targeted CCT program like the FSPs is likely to face. On one hand, the FSPs were successful as it substantially increased the secondary school enrollment rate by 15 percentage points or more. Even though the secondary enrollment rate for girls historically lagged far behind that for boys, girls have overtaken boys soon after the nationwide rollout of the FSPs. This demonstrates that incentives work.

On the other hand, our results also suggest that the quality of education for girls continued to lag behind that for boys among school enrollees because of the lack of investment in quality. As a result, girls' observable educational outcomes have also been worse than boys'. As shown in Figure 1, girls underperformed boys both in the passing rate and share of top students in the SSC examination. Further, conditional on the primary school completion, girls are less likely to graduate from secondary school on time. Therefore, our results clearly show that the narrowing of the gender gap in the quantity of education does not translate into the narrowing of the gender gap in the quality of education.

The findings of this study offer three important policy implications. First, CCT programs have a potential to narrow the gender gap in enrollment, even in a traditionally patriarchal country like Bangladesh, by providing households with adequate incentives to send girls to schools. Second, despite the first point, the quantity of education as measured by enrollment or years of education does not tell the whole story about the gender gap in education, because the incentive to increase the quantity of education does not necessarily lead to an improvement in the quality of education. On the contrary, CCT programs like the FSPs may directly reduce the quality of school education if they make classrooms overcrowded. This may increase the households' dependence on private tutoring and would exacerbate the female disadvantage because of the promale intrahousehold allocation of educational resources.[26] Therefore, policymakers must be aware of this limitation and consider implementing complementary policies.

Third, it would not be possible to truly achieve gender equality in education without addressing

[26]There is some suggestive evidence on the link connection between the FSP intensity and private tutoring. Based on the regressions of the use and amount of spending of private tutoring on the FSP intensity as measured by GRR, we find i) both girls and boys are more likely to have private tutoring in more FSP-intensive areas, ii) the share of the expenditure on private tutoring in the total expenditure for girls tends to be lower than that for boys conditional on the use of private tutoring, and iii) this gender gap is larger in more FSP-intensive areas in 2000 and 2005 (see footnote21 for the reason of the choice of these years). Even though the sign is consistent between these two years, we refrain from drawing strong conclusions because the estimates are not always statistically significant and because we do not observe the teacher-student ratio in the schools children attend.

the gender gap in the investment in the quality of education by households, as apparent from the underperformance of girls in secondary schools. Arguably, the quality is more difficult to address than the quantity, because the factors affecting the former—such as labor market returns and inherent gender bias among parents—may be beyond the control of those who make education policies. Nevertheless, interventions that are targeted to improve the access to education of better quality among disadvantages groups (e.g., voucher program in India (Muralidharan and Sundararaman, 2015)) or those that improve some supply factors for girls may narrow the gender gap in the quality of education.

There is indeed a piece of indicative evidence from a field experiment in Bangladesh. An impact assessment of the additional class teacher (ACT) program—in which teachers are hired to teach regular and additional supplementary classes in undeserved and low-performing areas—demonstrates positive impacts on the learning performance and the impact is particularly strong for girls (World Bank, 2018, Table 7.5). Further, anecdotal evidence suggests significant reduction in the prevalence of private coaching practices at schools where ACTs are operating (World Bank, 2018, p. 33). Hence, it seems possible to move towards gender equality in the quality of education, if policies are implemented to ensure quality education, particularly for those who are disadvantaged.

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Appendix

A Derivation of the likelihood function for the three-part model

In total, there are four separate cases to consider to construct the likelihood function for the three-part model:

Case 1: $d = 0$.

$$l_1 = P(\varepsilon_d \leq -x'_d\beta_d) = \Phi(-x'_d\beta_d).$$

Case 2: $d = 1, s = 0$.

$$l_2 = \frac{1}{y} P(-\varepsilon_d \leq x'_d\beta_d, \varepsilon_s \leq -x'_s\beta_s |\ \varepsilon_y = \log(y) - x'_y\beta_y) \cdot f(\log(y) - x'_y\beta_y),$$

where $f(\cdot)$ is the density function of ε_y.

We rearrange the distribution of the error terms as follows:

$$\begin{bmatrix} -\varepsilon_d \\ \varepsilon_s \\ \varepsilon_y \end{bmatrix} \sim N\left(\mathbf{0}, \begin{bmatrix} 1 & -\rho_{ds}\sigma_s & -\rho_{dy}\sigma_y \\ -\rho_{ds}\sigma_s & \sigma_s^2 & \rho_{ys}\sigma_y\sigma_s \\ -\rho_{dy}\sigma_y & \rho_{ys}\sigma_y\sigma_s & \sigma_y^2. \end{bmatrix}\right).$$

$(-\varepsilon_d, \varepsilon_s)'$ given ε_y follows a bivariate normal distribution with:

$$\mathbf{E}\left(\begin{pmatrix} -\varepsilon_d \\ \varepsilon_s \end{pmatrix} \middle| \varepsilon_y\right) = \begin{pmatrix} 0 \\ 0 \end{pmatrix} + \begin{pmatrix} -\rho_{dy}\sigma_y \\ \rho_{ys}\sigma_y\sigma_s \end{pmatrix} \frac{1}{\sigma_y^2}(\varepsilon_y - 0) = \begin{pmatrix} -\frac{\rho_{dy}}{\sigma_y}\varepsilon_y \\ \frac{\rho_{ys}\sigma_s}{\sigma_y}\varepsilon_y \end{pmatrix},$$

and

$$\mathbf{Var}\left(\begin{pmatrix} -\varepsilon_d \\ \varepsilon_s \end{pmatrix} \middle| \varepsilon_y\right) = \begin{pmatrix} 1 & -\rho_{ds}\sigma_s \\ -\rho_{ds}\sigma_s & \sigma_s^2 \end{pmatrix} - \begin{pmatrix} -\rho_{dy}\sigma_y \\ \rho_{ys}\sigma_y\sigma_s \end{pmatrix} \frac{1}{\sigma_y^2} \begin{pmatrix} -\rho_{dy}\sigma_y & \rho_{ys}\sigma_y\sigma_s \end{pmatrix}$$

$$= \begin{pmatrix} 1 - \rho_{dy}^2 & (\rho_{dy}\rho_{ys} - \rho_{ds})\sigma_s \\ (\rho_{dy}\rho_{ys} - \rho_{ds})\sigma_s & (1 - \rho_{ys}^2)\sigma_s^2 \end{pmatrix}.$$

Then, we have:

$$P(-\varepsilon_d \leq x'_d\beta_d, \varepsilon_s \leq -x'_s\beta_s |\ \varepsilon_y = \log(y) - x'_y\beta_y)$$

$$= \Psi\left(\frac{x'_d\beta_d + \rho_{dy}\varepsilon_y/\sigma_y}{\sqrt{1-\rho_{dy}^2}}, -\frac{x'_s\beta_s + \rho_{ys}\sigma_s\varepsilon_y/\sigma_y}{\sigma_s\sqrt{1-\rho_{ys}^2}}, \frac{\rho_{dy}\rho_{ys} - \rho_{ds}}{\sqrt{(1-\rho_{dy}^2)(1-\rho_{ys}^2)}}\right),$$

and

$$f(\log(y) - x'_y\beta_y) = \frac{1}{\sigma_y}\phi(\frac{\log(y) - x'_y\beta_y}{\sigma_y}).$$

Thus, the likelihood for this case is:

$$l_2 = \frac{\phi(e_y)}{y\sigma_y} \cdot \Psi\left(\frac{x'_d\beta_d + \rho_{dy}e_y}{\sqrt{1-\rho_{dy}^2}}, -\frac{x'_s\beta_s + \rho_{ys}\sigma_s e_y}{\sigma_s\sqrt{1-\rho_{ys}^2}}, \frac{\rho_{dy}\rho_{ys} - \rho_{ds}}{\sqrt{(1-\rho_{dy}^2)(1-\rho_{ys}^2)}}\right).$$

Case 3: $d = 1, s \in (0,1)$.

$$l_3 = \frac{1}{y}P(-\varepsilon_d \leq x'_d\beta_d |\ \varepsilon_y = \log(y) - x'_y\beta_y, \varepsilon_s = s - x'_s\beta_s) \cdot g(\log(y) - x'_y\beta_y, s - x'_s\beta_s),$$

where $g(\cdot,\cdot)$ is the joint density function for ε_y and ε_s.

Let the submatrix Σ_{11} be

$$\Sigma_{11} = \begin{pmatrix} \sigma_y^2 & \rho_{ys}\sigma_y\sigma_s \\ \rho_{ys}\sigma_y\sigma_s & \sigma_s^2 \end{pmatrix}.$$

Thus, we have

$$\Sigma_{11}^{-1} = \frac{1}{(1-\rho_{ys}^2)\sigma_y^2\sigma_s^2}\begin{pmatrix} \sigma_s^2 & -\rho_{ys}\sigma_y\sigma_s \\ -\rho_{ys}\sigma_y\sigma_s & \sigma_y^2 \end{pmatrix},$$

where the determinant of Σ_{11} is $|\Sigma_{11}| = (1-\rho_{ys}^2)\sigma_y^2\sigma_s^2$.

It can be shown that $-\varepsilon_d$ given ε_y and ε_s follows a normal distribution with:

$$\mathbf{E}\left(-\varepsilon_d|\varepsilon_y, \varepsilon_s\right) = 0 + \frac{1}{|\Sigma_{11}|}(-\rho_{dy}\sigma_y \quad -\rho_{ds}\sigma_s)\begin{pmatrix} \sigma_s^2 & -\rho_{ys}\sigma_y\sigma_s \\ -\rho_{ys}\sigma_y\sigma_s & \sigma_y^2 \end{pmatrix}\begin{pmatrix} \varepsilon_y \\ \varepsilon_s \end{pmatrix}$$

$$= -\frac{1}{(1-\rho_{ys}^2)\sigma_y^2\sigma_s^2}\left((\rho_{dy} - \rho_{ds}\rho_{ys})\sigma_y\sigma_s^2 \quad (\rho_{ds} - \rho_{dy}\rho_{ys})\sigma_y^2\sigma_s)\right)\begin{pmatrix} \varepsilon_y \\ \varepsilon_s \end{pmatrix}$$

$$= -\frac{(\rho_{dy} - \rho_{ds}\rho_{ys})\sigma_s\varepsilon_y + (\rho_{ds} - \rho_{dy}\rho_{ys})\sigma_y\varepsilon_s}{(1-\rho_{ys}^2)\sigma_y\sigma_s},$$

and

$$\mathbf{Var}\left(-\varepsilon_d|\varepsilon_y,\varepsilon_s\right) = 1-\frac{1}{|\Sigma_{11}|}\begin{pmatrix}-\rho_{dy}\sigma_y & -\rho_{ds}\sigma_s\end{pmatrix}\begin{pmatrix}\sigma_s^2 & -\rho_{ys}\sigma_y\sigma_s\\ -\rho_{ys}\sigma_y\sigma_s & \sigma_y^2\end{pmatrix}\begin{pmatrix}-\rho_{dy}\sigma_y\\ -\rho_{ds}\sigma_s\end{pmatrix}$$

$$= 1-\frac{1}{(1-\rho_{ys}^2)\sigma_y^2\sigma_s^2}\begin{pmatrix}-(\rho_{dy}-\rho_{ds}\rho_{ys})\sigma_y\sigma_s^2 & -(\rho_{ds}-\rho_{dy}\rho_{ys})\sigma_y^2\sigma_s\end{pmatrix}\begin{pmatrix}-\rho_{dy}\sigma_y\\ -\rho_{ds}\sigma_s\end{pmatrix}$$

$$= 1-\frac{(\rho_{dy}-\rho_{ds}\rho_{ys})\rho_{dy}+(\rho_{ds}-\rho_{dy}\rho_{ys})\rho_{ds}}{(1-\rho_{ys}^2)}$$

$$= \frac{1-\rho_{ys}^2-\rho_{dy}^2-\rho_{ds}^2+2\rho_{dy}\rho_{ds}\rho_{ys}}{1-\rho_{ys}^2}.$$

We then have

$$P(-\varepsilon_d \le x'_d\beta_d|\ \varepsilon_y = \log(y)-x'_y\beta_y, \varepsilon_s = s-x'_s\beta_s)$$

$$= \Phi\left(\frac{x'_d\beta_d(1-\rho_{ys}^2)+(\rho_{dy}-\rho_{ds}\rho_{ys})(\log(y)-x'_y\beta_y)/\sigma_y+(\rho_{ds}-\rho_{dy}\rho_{ys})(s-x'_s\beta_s)/\sigma_s}{\sqrt{(1-\rho_{ys}^2-\rho_{dy}^2-\rho_{ds}^2+2\rho_{dy}\rho_{ds}\rho_{ys})(1-\rho_{ys}^2)}}\right),$$

and

$$g(\varepsilon_y,\varepsilon_s) = g(\log(y)-x'_y\beta_y, s-x'_s\beta_s)$$

$$= \frac{1}{2\pi\sigma_y\sigma_s\sqrt{1-\rho_{ys}^2}}\exp\left[-\frac{1}{2}\begin{pmatrix}\varepsilon_y & \varepsilon_s\end{pmatrix}\frac{1}{|\Sigma_{11}|}\begin{pmatrix}\sigma_s^2 & -\rho_{ys}\sigma_y\sigma_s\\ -\rho_{ys}\sigma_y\sigma_s & \sigma_y^2\end{pmatrix}\begin{pmatrix}\varepsilon_y\\ \varepsilon_s\end{pmatrix}\right]$$

$$= \frac{1}{2\pi\sigma_y\sigma_s\sqrt{1-\rho_{ys}^2}}\exp\left[-\frac{\varepsilon_y^2\sigma_s^2-2\rho_{ys}\sigma_y\sigma_s\varepsilon_y\varepsilon_s+\varepsilon_s^2\sigma_y^2}{2(1-\rho_{ys}^2)\sigma_y^2\sigma_s^2}\right]$$

$$= \frac{1}{\sigma_y\sigma_s\sqrt{1-\rho_{ys}^2}}\phi\left(\frac{\varepsilon_y}{\sigma_y\sqrt{1-\rho_{ys}^2}}\right)\phi\left(\frac{\varepsilon_s}{\sigma_s\sqrt{1-\rho_{ys}^2}}\right)\exp\left(\rho_{ys}\frac{\varepsilon_y\varepsilon_s}{(1-\rho_{ys}^2)\sigma_y\sigma_s}\right)$$

$$= \frac{1}{\sigma_y\sigma_s\sqrt{1-\rho_{ys}^2}}\phi\left(\frac{\log(y)-x'_y\beta_y}{\sigma_y\sqrt{1-\rho_{ys}^2}}\right)\phi\left(\frac{s-x'_s\beta_s}{\sigma_s\sqrt{1-\rho_{ys}^2}}\right)\exp\left(\rho_{ys}\frac{(\log(y)-x'_y\beta_y)(s-x'_s\beta_s)}{(1-\rho_{ys}^2)\sigma_y\sigma_s}\right).$$

Thus, the likelihood for this case is:

$$l_3 = \frac{1}{y\sigma_y\sigma_s\sqrt{1-\rho_{ys}^2}}\Phi\left(\frac{x'_d\beta_d(1-\rho_{ys}^2)+(\rho_{dy}-\rho_{ds}\rho_{ys})e_y+(\rho_{ds}-\rho_{dy}\rho_{ys})e_s}{\sqrt{(1-\rho_{ys}^2-\rho_{dy}^2-\rho_{ds}^2+2\rho_{dy}\rho_{ds}\rho_{ys})(1-\rho_{ys}^2)}}\right)$$

$$\cdot\,\phi\left(\frac{e_y}{\sqrt{1-\rho_{ys}^2}}\right)\phi\left(\frac{e_s}{\sqrt{1-\rho_{ys}^2}}\right)\exp\left(\rho_{ys}\frac{e_ye_s}{1-\rho_{ys}^2}\right).$$

Case 4: $d = 1, s = 1$.

$$l_4 = \frac{1}{y} P(-\varepsilon_d \le x'_d\beta_d, -\varepsilon_s \le x'_s\beta_s - 1 |\, \varepsilon_y = \log(y) - x'_y\beta_y) \cdot f(\log(y) - x'_y\beta_y)$$

We rearrange the distribution of the error terms as follows:

$$\begin{bmatrix} -\varepsilon_d \\ -\varepsilon_s \\ \varepsilon_y \end{bmatrix} \sim N\left(\mathbf{0}, \begin{bmatrix} 1 & \rho_{ds}\sigma_s & -\rho_{dy}\sigma_y \\ \rho_{ds}\sigma_s & \sigma_s^2 & -\rho_{ys}\sigma_y\sigma_s \\ -\rho_{dy}\sigma_y & -\rho_{ys}\sigma_y\sigma_s & \sigma_y^2 \end{bmatrix}\right).$$

$(-\varepsilon_d, -\varepsilon_s)^T$ given ε_y follows bivariate normal distribution with:

$$\mathbf{E}\left(\begin{pmatrix} -\varepsilon_d \\ -\varepsilon_s \end{pmatrix} \middle|\, \varepsilon_y\right) = \begin{pmatrix} 0 \\ 0 \end{pmatrix} + \begin{pmatrix} -\rho_{dy}\sigma_y \\ -\rho_{ys}\sigma_y\sigma_s \end{pmatrix} \frac{1}{\sigma_y^2}(\varepsilon_y - 0) = \begin{pmatrix} -\frac{\rho_{dy}}{\sigma_y}\varepsilon_y \\ -\frac{\rho_{ys}\sigma_s}{\sigma_y}\varepsilon_y \end{pmatrix},$$

and

$$\mathbf{Var}\left(\begin{pmatrix} -\varepsilon_d \\ -\varepsilon_s \end{pmatrix} \middle|\, \varepsilon_y\right) = \begin{pmatrix} 1 & \rho_{ds}\sigma_s \\ \rho_{ds}\sigma_s & \sigma_s^2 \end{pmatrix} - \begin{pmatrix} -\rho_{dy}\sigma_y \\ -\rho_{ys}\sigma_y\sigma_s \end{pmatrix} \frac{1}{\sigma_y^2} \begin{pmatrix} -\rho_{dy}\sigma_y & -\rho_{ys}\sigma_y\sigma_s \end{pmatrix}$$

$$= \begin{pmatrix} 1 & \rho_{ds}\sigma_s \\ \rho_{ds}\sigma_s & \sigma_s^2 \end{pmatrix} - \begin{pmatrix} \rho_{dy}^2 & \rho_{dy}\rho_{ys}\sigma_s \\ \rho_{dy}\rho_{ys}\sigma_s & \rho_{ys}^2\sigma_s^2 \end{pmatrix}$$

$$= \begin{pmatrix} 1 - \rho_{dy}^2 & (\rho_{ds} - \rho_{dy}\rho_{ys})\sigma_s \\ (\rho_{ds} - \rho_{dy}\rho_{ys})\sigma_s & (1 - \rho_{ys}^2)\sigma_s^2 \end{pmatrix}.$$

Then, we have

$$P(-\varepsilon_d \le x'_d\beta_d, -\varepsilon_s \le x'_s\beta_s - 1 |\, \varepsilon_y = \log(y) - x'_y\beta_y)$$

$$= \Psi\left(\frac{x'_d\beta_d + \rho_{dy}(\log(y) - x'_y\beta_y)/\sigma_y}{\sqrt{1-\rho_{dy}^2}}, \frac{x'_s\beta_s - 1 + \rho_{ys}\sigma_s(\log(y) - x'_y\beta_y)/\sigma_y}{\sigma_s\sqrt{1-\rho_{ys}^2}}, \frac{\rho_{ds} - \rho_{dy}\rho_{ys}}{\sqrt{(1-\rho_{dy}^2)(1-\rho_{ys}^2)}}\right),$$

and

$$f(\log(y) - x'_y\beta_y) = \frac{1}{\sigma_y}\phi\left(\frac{\log(y) - x'_y\beta_y}{\sigma_y}\right).$$

Thus, the likelihood for this case is:

$$l_4 = \frac{\phi(e_y)}{y\sigma_y} \cdot \Psi\left(\frac{x'_d\beta_d + \rho_{dy}e_y}{\sqrt{1-\rho_{dy}^2}}, \frac{x'_s\beta_s - 1 + \rho_{ys}\sigma_s e_y}{\sigma_s\sqrt{1-\rho_{ys}^2}}, \frac{\rho_{ds} - \rho_{dy}\rho_{ys}}{\sqrt{(1-\rho_{dy}^2)(1-\rho_{ys}^2)}}\right),$$

where $e_y = \frac{\log(y) - x'_y \beta_y}{\sigma_y}$ and $e_s = \frac{s - x'_s \beta_s}{\sigma_s}$.

B Derivation of marginal effects

The equation for the expected enrollment is straightforward. The equation for the conditional expenditure can be derived as follows:

$$
\begin{aligned}
E(y|d=1) &= \int_0^\infty y f(y|d=1) dy = \int_0^\infty y f(y|\varepsilon_d > -x'_d \beta_d) dy \\
&= \int_0^\infty y \frac{1}{y} f(\varepsilon_y|\varepsilon_d > -x'_d \beta_d) dy = \int_0^\infty \frac{f(\varepsilon_y, \varepsilon_d > -x'_d \beta_d)}{P(\varepsilon_d > -x'_d \beta_d)} dy \\
&= \int_0^\infty \frac{f(\varepsilon_d > -x'_d \beta_d | \varepsilon_y) f(\varepsilon_y)}{P(\varepsilon_d > -x'_d \beta_d)} dy \\
&= \int_0^\infty \frac{\Phi\left(\frac{x'_d \beta_d + \rho_{dy} \varepsilon_y / \sigma_y}{\sqrt{1-\rho_{dy}^2}}\right) \phi\left(\frac{\varepsilon_y}{\sigma_y}\right) / \sigma_y}{\Phi(x'_d \beta_d)} dy,
\end{aligned}
$$

where $\varepsilon_y = \log(y) - x'_y \beta_y$.

The unconditional expectation of y is:

$$
E(y) = P(d=1) E(y|d=1) = \int_0^\infty \frac{1}{\sigma_y} \Phi\left(\frac{x'_d \beta_d + \rho_{dy} \varepsilon_y / \sigma_y}{\sqrt{1-\rho_{dy}^2}}\right) \phi\left(\frac{\varepsilon_y}{\sigma_y}\right) dy.
$$

Unconditional expectation of the core expenditure ys is:

$$
\begin{aligned}
E(ys) &= \int_0^1 \int_0^\infty ys f(y,s) dy ds \\
&= \int_0^\infty y \cdot 1 \cdot f(d=1, y, s=1) dy + \int_0^1 \int_0^\infty ys f(d=1, y, s) dy ds \\
&= \int_0^\infty \frac{1}{\sigma_y} \phi\left(\frac{\varepsilon_y}{\sigma_y}\right) \Psi\left(\frac{x'_d \beta_d + \rho_{dy} \varepsilon_y / \sigma_y}{\sqrt{1-\rho_{dy}^2}}, \frac{x'_s \beta_s - 1 + \rho_{ys} \sigma_s \varepsilon_y / \sigma_y}{\sigma_s \sqrt{1-\rho_{ys}^2}}, \frac{\rho_{ds} - \rho_{dy} \rho_{ys}}{\sqrt{(1-\rho_{dy}^2)(1-\rho_{ys}^2)}}\right) dy \\
&+ \int_0^1 \int_0^\infty ys \frac{1}{y \sigma_y \sigma_s \sqrt{1-\rho_{ys}^2}} \Phi\left(\frac{x'_d \beta_d (1-\rho_{ys}^2) + (\rho_{dy} - \rho_{ds} \rho_{ys}) \varepsilon_y / \sigma_y + (\rho_{ds} - \rho_{dy} \rho_{ys}) \varepsilon_s / \sigma_s}{\sqrt{(1-\rho_{ys}^2 - \rho_{dy}^2 - \rho_{ds}^2 + 2\rho_{dy} \rho_{ds} \rho_{ys})(1-\rho_{ys}^2)}}\right) \\
&\times \phi\left(\frac{\varepsilon_y}{\sigma_y \sqrt{1-\rho_{ys}^2}}\right) \phi\left(\frac{\varepsilon_s}{\sigma_s \sqrt{1-\rho_{ys}^2}}\right) \exp\left(\rho_{ys} \frac{\varepsilon_y \varepsilon_s}{\sigma_y \sigma_s (1-\rho_{ys}^2)}\right) dy ds,
\end{aligned}
$$

where $\varepsilon_s = s - x'_s \beta_s$.

The expectation of the core expenditure conditional on enrollment is:

$$E(ys|d=1) = \frac{E(ys)}{P(d=1)} = \frac{E(ys)}{\Phi(x'_d\beta_d)}.$$

We compute the conditional and unconditional expectations at the sample mean by replacing the parameters (θ) with the ML estimates ($\hat{\theta}_{ML}$) given covariates. The marginal effect of being a girl is computed by taking the difference in these expectations when the girl dummy is set equal to zero and when it is equal to one.

We obtain the standard errors for the marginal effects by the following simulation. We first draw the parameter θ from a multivariate normal distribution, where its mean and variance respectively follow the point estimate and its variance-covariance matrix from the ML estimation. We then calculate the marginal effects again with the drawn value of θ using the expressions above. By repeating this 100 times and taking the standard deviation of the estimates of the marginal effect across replications, we obtain a standard error.

In principle, we can calculate the marginal effect for each observation and then calculate the average marginal effect over all observations. However, we choose to calculate only the marginal effects at the sample mean, where the sample mean of the whole sample [subsample of secondary school enrollees] is used for the marginal effects on the probability of enrollment and unconditional quantities [conditional quantities] to reduce the computational burden.[27]

C Tuition and quality of education

To understand the relationship between the tuition fee and quality of education, we would ideally run a regression of tuition fee on an indicator of education quality. However, we do not have school-level data that can be linked to HES/HIES data. Instead, we run a regression of the average test score on the average tuition per student at the school level using the datasets for the Comparing Food versus Cash for Education (FFE-CFE) program for the years 2000 and 2003 collected by the International Food Policy Research Institute.[28] While these data are available only for primary schools, this is the only dataset to our knowledge that allows us to link the tuition fee and educational outcome in Bangladesh.

Figure 5 is a scatter plot between the average tuition per student and average test scores at the school level in 2000 and 2003. As this figure shows, the average test score is higher in schools that

[27] Matlab was used for computation of the marginal effects and STATA was used in the rest of the analysis.

[28] The details of the FFE-CFE program datasets is available from https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/15640 and https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/ 15580 accessed on December 12, 2017.

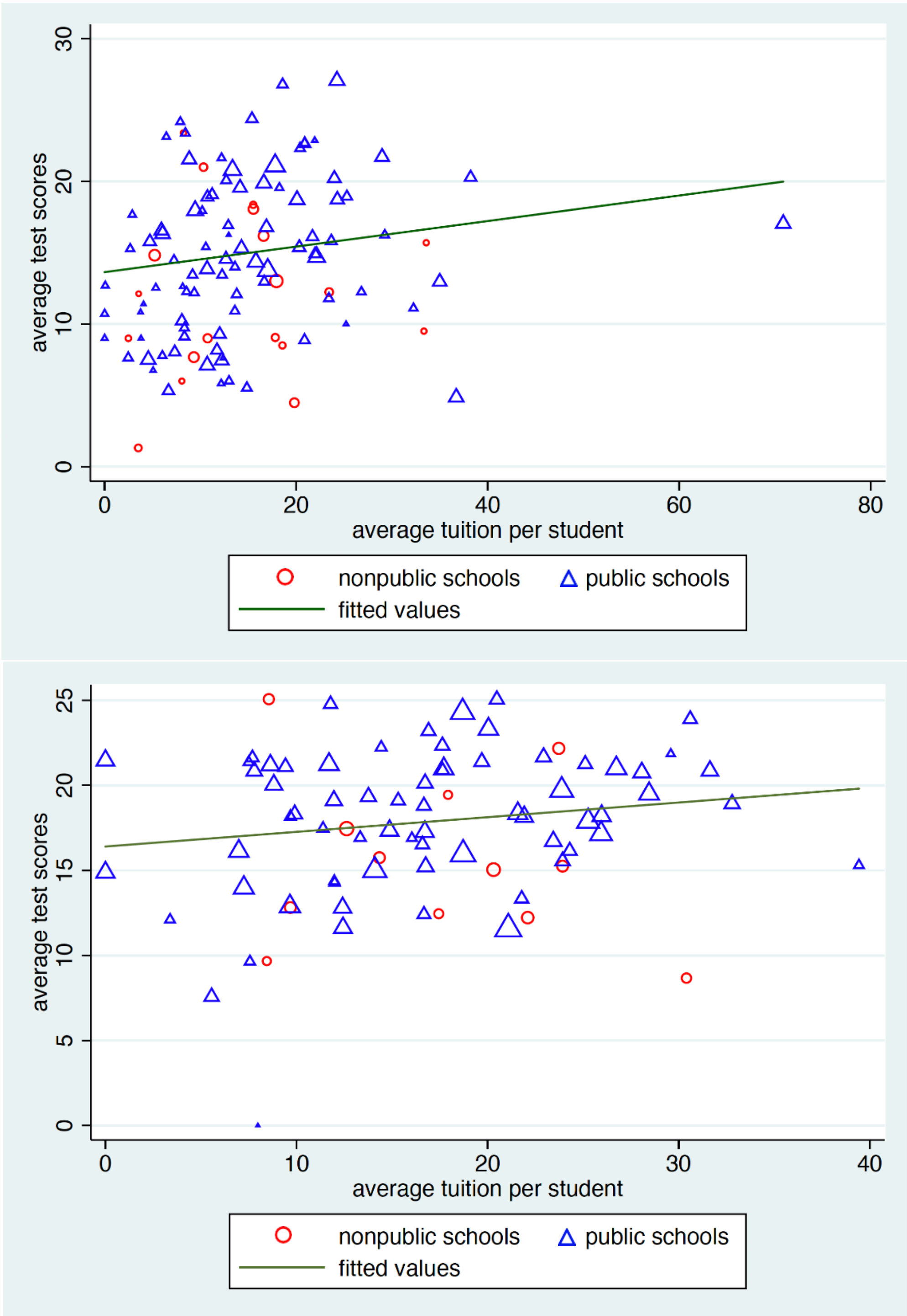

Figure 5: The scatter plot of the average test score and the average tuition fee charged by the school for the years 2000 (top) and 2003 (bottom) based on the FFE-CFE data. Each blue triangle [red circle] represents a public [nonpublic] school, and the size of each marker is proportionate to the number of enrolled students in the school. The green lines represent the linear fits (weighted), and their slopes are significantly different from 0 at a 10 percent level.

impose a higher tuition in both years. Clearly, this should not be taken as definitive evidence that higher tuition reflects higher educational quality at the secondary level for a number of reasons. First, the data we use here are for the primary level and not the secondary level. This distinction may matter because private schools at the primary level are not as common as they are at the secondary level. Second, the data are not nationally representative and the sample selection may be an issue. Third, we do not consider the effect of endogenous school choice; it may be the case that those children with parents who can afford to pay a high tuition are those with high innate ability or those who receive complementary private tutoring. Nevertheless, Figure 5 is consistent with the possibility that higher tuition reflects higher educational quality.

It should be noted that the tuition fee is not a simple reflection of school type. In the FFE-CFE data, there is indeed a substantial variation in the tuition per student both in private and public schools as Figure 5 shows. Correspondingly, there appear to be significant variations in quality within each type. Casual observations of schools indicate that most of the top schools are private in Bangladesh. On the other hand, the BANBEIS database suggests that private schools are smaller and of lower quality than public schools on average. For example, the average quality of teachers in private schools is worse than that of public schools as measured by the fraction of trained teachers.[29] Student-teacher ratios for private schools were, if anything, slightly higher than those for public schools at the secondary level in the past, even though they are very similar today.[30] Therefore, the average quality of private schools appears to be lower than that of public schools.

D Falsification test

To support the findings on the impact of the FSPs on the quantity measures of education in Section 6, we conduct a falsification test. Our strategy is to estimate the FSPs' impacts on the years of completed education and enrollment, if the year of introduction of the FSPs were hypothetically moved earlier by five years. We chose five years to balance the number of observations before and after the hypothetical introduction of the FSPs without losing too many observations. To make a fair comparison between the estimates based on the actual year and hypothetical year (i.e., five years prior to the actual year) of introduction of the FSPs, we first construct two estimation samples, one for each of the actual and hypothetical years.

We choose the individuals aged 16-20 and compare them with those aged 21-26 in the actual year of introduction of the FSPs, where the former and latter groups serve as the treatment and comparison

[29] According to BANBEIS (2010), 84 percent [78 percent] of teachers are trained in public [private] school in 2010.

[30] This is not true at the primary level. Private schools are smaller and student-teacher ratios in private schools are much lower than those in public schools.

groups for the purpose of the falsification test. Neither groups are likely to have benefitted substantially from the FSPs as they are already past the official secondary-school age, even though a small fraction of those in the treatment group may have benefitted from the FSPs due to delayed entry into school and grade repetition. To conduct the falsification test, we move forward the year of introduction of the FSPs by five years so that the individuals in the (hypothetical) comparison [treatment] group are aged 16-20 [11-15] in the hypothetical year of the introduction of the FSPs.

Since the falsification sample is produced by restricting each of the treatment and comparison groups to a set of individuals who were born within a five-year band, we also re-estimate the impacts of the FSPs on the quantity measures of education by applying a similar sample restriction to make a fair comparison. Specifically, we choose the individuals aged 6-10 [16-20] for the treatment [comparison] group in the actual year of introduction of the FSPs to estimate the actual impact of the FSPs. Note that we chose not to use those aged 11-15 because they are not fully covered by the FSPs; this is an approach similar to that of Duflo (2001).

In this section, we focus on the analyses of HIES 2005 and 2010, because many of those aged 6-10 at the time of the nationwide rollout of the FSPs in 1994 have not completed their education in 1995 and 2000 as they are still aged, respectively, 7-11 and 12-16 in 1995 and 2000. For the analysis of the completed years of education, we simply take all individuals satisfying the age criteria discussed above. For the analysis of enrollment, we take the retrospectively-constructed enrollment records corresponding to ages 11-15.

In the odd-numbered columns in Table 14, we report the estimation results based on the actual year of introduction of FSPs. They serve as our benchmarks and are quantitatively and qualitatively comparable to those reported in Table 8. While the point estimates appear to be somewhat attenuated and standard errors tend to be larger than those reported in Table 8, these are to be expected because those who are aged 16-20 may benefit from the FSPs and the sample size used in Table 14 is smaller.

In the even numbered columns, we report the results of the falsification test, where the year introduction of the FSPs are set at the hypothetical year, or five years prior to the actual year of introduction. As expected, none of the coefficients is positive and significant, and all coefficients are smaller in absolute value than those reported in the odd numbered columns. Therefore, our falsification test provides suggestive evidence that the estimated positive effects of the FSPs on the quantity measures of education are not spurious. In particular, they are unlikely to be driven by subdistrict-specific time trends that are correlated with the rollout of the FSPs. Thus, the results in Table 8 indeed appear to be driven by the rollout of FSPs.

Table 14: Impacts of the FSPs on the quantity measures of education

	HIES 2005		HIES 2010	
	Actual	Hypothetical	Actual	Hypothetical
Coef	(1)	(2)	(3)	(4)
Panel A: Years of education				
Girl	-1.037***	-0.917***	-1.327***	-0.842**
	(0.260)	(0.293)	(0.314)	(0.380)
FSP Cover	-0.784	-0.348	-1.298	0.406
	(1.110)	(0.619)	(1.255)	(0.599)
Girl × FSPCover	1.310***	0.019	1.533***	-0.346
	(0.393)	(0.378)	(0.363)	(0.527)
Obs	5,669	6,963	8,898	7,324
Mean of dep. var.	5.268	4.260	5.204	4.020
Panel B: Enrollment using retrospective data				
Girl	-0.117***	-0.081***	-0.148***	-0.079**
	(0.025)	(0.029)	(0.031)	(0.038)
FSP Cover	-0.098	-0.082	-0.092	-0.037
	(0.163)	(0.082)	(0.135)	(0.062)
Girl × FSPCover	0.154***	0.009	0.172***	-0.027
	(0.030)	(0.040)	(0.036)	(0.053)
Obs	38,985	34,815	44,490	36,620
Mean of dep. var.	0.401	0.297	0.360	0.272

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. In Panel A, we additionally include the fixed-effects terms specific to the birth year and household. In Panel B, we additionally include the fixed-effects terms specific to the birth year, age at the time of observation, household, and year of observation.

E Comparison with Heath and Mobarak (2015) estimates

As mentioned in Section 6, our finding of a positive impact of the FSPs on enrollment is notably at odds with Heath and Mobarak (2015, hereafter HM), who found no evidence that the FSPs have a positive impact on female enrollment. Therefore, we investigate the source of inconsistency between our results and theirs. To this end, we start with their data and specification and gradually change various elements of HM's analysis to arrive at our preferred estimate within the framework of the triple difference estimation used by HM. We argue that our preferred estimate is more suitable as an estimate of the impact of the FSPs on school enrollment in Bangladesh than HM's estimate.

The identification of the impact of the FSPs in the HM's analysis relies on the triple difference approach, which is somewhat similar to the double differences specification in eq. (6). However, in addition to the differences between the two genders and between those who are in the subdistrict covered by FSP at the time of observation and those who are not, the HM's analysis also includes the data for the primary-school age group and takes the third difference between the FSP-eligible and

FSP-ineligible individuals, essentially using the fact that primary school children would not directly benefit from the FSPs. Therefore, the generic triple difference specification we use for the comparison of our preferred specification with HM can be written as follows:

$$
\begin{aligned}
Enroll_{iht} &= \alpha_1 Girl_{ih} + \alpha_2 FSPCover_{iht} + \alpha_3 Eligible_{iht} + \alpha_4 FSPCover_{iht} \times Eligible_{iht} \\
&\quad + \alpha_5 Girl_{ih} \times FSPCover_{iht} + \alpha_6 Eligible_{iht} \times Girl_{ih} \\
&\quad + \alpha_7 FSPCover_{iht} \times Eligible_{iht} \times Girl_{ih} + \lambda_t^0 + \lambda_t^1 \times Girl_{ih} + \sum_{a=5}^{a=18} \beta_a^0 \times \mathbf{1}(Age = a) \\
&\quad + \textstyle\sum_{a=5}^{a=18} \beta_a^1 \times \mathbf{1}(Age = a) \times Girl_{ih} + \theta_h + \varepsilon_{iht}, \qquad (7)
\end{aligned}
$$

where Eligible$_{iht}$ is the dummy variable for the FSP eligibility and βs, λs, and θ_h represent, respectively, agegender-, time-gender-, and household-specific fixed effects. α_7 is the coefficient of our main interest.

Let us now highlight three major differences between HM's specification and our preferred specification in the triple difference framework. First, the definition of FSPCover$_{iht}$ is different. In HM, it is an indicator for the year 1994 or later ("P94"), which is a reasonable choice because the FSP was scaled up significantly in 1994 and all four subdistricts in the HM's data (See Appendix B of Heath and Mobarak (2015)) were indeed first covered by the FSPs in 1994. However, in our preferred specification, we take into account the full information ("Full") about the rollout of the FSPs to address the fact that some subdistricts were covered by the FSPs before 1994. Second, the definition of Eligible$_{iht}$ is also different. In HM, it is an indicator for having completed at least 6 years of schooling at the time of observation, which means that the individual has already completed the first year of secondary school. In our preferred specification, we instead define Eligible$_{iht}$ as an indicator for having completed a primary school, or five years of education. We argue that this is a more suitable definition, because individuals would make an enrollment decision taking into account whether they would benefit from the FSPs *if* they enroll. Finally, the data are different. In particular, HM's data were collected in 2009 and only cover 4 subdistricts ("HM4"), but our preferred specification uses all districts ("All") included in the nationally-representative HIES 2010 dataset.

To ensure the maximum comparability, we construct the retrospective panel data on enrollment both from the HM's data and HIES 2010 using the same rule. As with the construction of the enrollment indicator for eq. (6), we construct the past enrollment status using the age and maximum educational attainment at the time of observation under the assumption of no grade repetition. Because we also include observations corresponding to the primary school children in this section, we do this exercise

Table 15: Effects of FSPs on school enrollment: comparison with HM

Data source	HM[a]		HIES 2010		
Dep var: $Enroll_{iht}$	(1)	(2)	(3)	(4)	(5)
	Panel A: Eligible is 6+ years of education				
FSPCover × Eligible ×Girl	-0.0097	-0.017	0.057	0.020**	0.017*
	(0.0609)	(0.059)	(0.056)	(0.009)	(0.009)
	Panel B: Eligible is primary school completion (5+ years of education)				
FSPCover × Eligible × Girl	—	0.046	0.100*	0.078***	0.078***
		(0.050)	(0.053)	(0.008)	(0.009)
Definition of FSPCover[b]	P94	P94	P94	P94	Full
Subdistricts in the sample[c]	HM4	HM4	HM4	All	All
Observations	23,129	23,116	9,216	517,039	517,039
No. of Individual	—	2,244	766	45,444	45,444
No. of Household	878	878	220	12,124	12,124

[a] Column (1) uses the enrollment data HM constructed (JDE HM data -- enrollment.dta). Column (2) uses educational attainment data (JDE HM data -- educational attainment.dta), which contain the age, gender, and highest educational attainment, but not the actual entry age in school. These two data cannot be merged because there is no individual identifier. As a result, we are unable to redefine $Eligible_{iht}$ to obtain an estimate for column (1) of Panel B. [b] In columns (1)–(4), the FSP coverage indicator ($FSPCover_{iht}$) is an indicator for the year 1994 or later ("P94"), whereas it uses full information ("Full") about the FSP rollout in column (5).
[c] The samples used in columns (1) – (3) cover the four districts in the HM data ("HM4"). Column (4) – (5) use all subdistricts ("All") in HIES 2010.
Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. The estimation is based on the OLS estimation of eq. (7). Standard errors clustered at the household level are reported in parentheses. The fixed-effects terms by the household, age-gender combination, age-year combination are included in all regressions. Further, FSPCover, Eligible, and Girl, and the interactions between any two of these three variables are also included.

under the assumption that all children start grade 1 at age 6. As with HM, we take all observations for those individuals who are aged between 5 and 18 at the time of observation and do this for the period between 1960 and 2007.

Table 15 provides the estimation results for eq. (7) based on different choices of data and definitions of $FSPCover_{iht}$ and $Eligible_{iht}$. In Panel A, we use at least six years of education as the FSP eligibility criterion to be consistent with HM. In Panel B, we use the primary school completion as the FSP eligibility criterion. Columns (1)-(3) use only HM4 subdistricts, whereas columns (4)-(5) use all subdistricts. Columns (1)-(4) use P94 for the definition of FSPCover, whereas column (5) uses full information.

In column (1) of Panel A, we reproduce the estimate of the FSP impact reported in HM, which uses the actual age at which the individual entered school. This estimate indeed suggests that the FSPs had no impact on enrollment. Because we do not observe the actual age of school entry in HIES, we have to make the assumption that children enters primary school at age 6. Based on this assumption, we reconstructed retrospective panel data on enrollment using the HM data and ran the same regression. As reported in column (2) of Panel A, the estimate remains similar. Therefore, our entry-age assumption does not appear to alter the results much.

Now, let us compare Panels A and B of column (2). While point estimates are both insignificant, it is worth noting that the point estimate is positive when the primary completion is used for the eligibility definition. Column (3) uses the HIES 2010 data instead of the HM data, but we focus on the HM4 subdistricts. While both data were randomly sampled and the difference between columns (2) and (3) is insignificant, it appears plausible that the sampling negatively affected the estimated FSP impact from the HM data relative to that from the HIES 2010 data.

In column (4), we expand the data to include all subdistricts. The larger sample size clearly allowed us to obtain a more accurate estimate. The point estimate is positive and significant whether we use HM's eligibility definition or ours. In column (5), we use the full information about the FSP rollout instead of P94. This change does not affect the results much as expected, because the FSP coverage started in 1994 for most individuals.

By comparing across the columns in Panel A, we see that both the choice of data and geographic coverage of the data (or sample size) appear to have affected HM's result. However, the primary difference between the HM's estimate and our preferred estimate reported in column (5) of Panel B comes from the definition of the eligibility criterion.

As we argued earlier, our choice of eligibility criterion is more suitable, because the FSPs makes it more attractive to keep girls enrolled in school after the completion of primary education. If we use at least six years of education, the FSPs' impact on the grade-6 student is absorbed by the non-eligible group. As a result, the FSPs' impact would be underestimated. It is therefore not surprising that there is a sizable difference between the estimates in Panels A and B in each column.

We also conducted a few robustness checks. First, we tested our results under the alternative school entry ages of 5 and 7, because not all children enter school at age 6. Second, instead of using the individuals aged between 5 and 18, we limit to the sample to ages 6 to 15 to follow the stipulated primary- and secondary-school age groups. These analyses do not qualitatively change our results.

It is worth noting that the magnitude of the estimated impact of the FSPs on enrollment is quantitatively different between Tables 8 and 15. The most comparable estimate, which uses the HIES 2010 data with household fixed effects reported in column (4) of Panel B of Table 8, suggests that the FSPs had a positive impact on enrollment by 19 percentage points. On the other hand, our preferred estimate in Table 15 suggests only around 8 percentage points.

We argue that the latter estimate would serve as a lower bound of the impact for the FSP's target age group for two reasons. First, by extending our earlier argument to use primary completion instead of at least 6 years of education as a more suitable eligibility criterion, it can be seen that the decision to enroll in a primary school is likely to be positively influenced by the FSPs that are available at the secondary level. This in turn means that the triple difference estimate would underestimate the impact of the FSPs. Second, the double difference estimate in Table 8 narrowly focuses on the secondary school students. On the other hand, the sample used in Table 15 include relatively old individuals, aged 16 to 18, who are not the main target age of the FSPs. For these reasons, we prefer the double difference estimates over triple difference estimates and use the former in the main text.

F Additional tables for summary statistics and detailed regression results

Tables 16 and 17 provide the same summary statistics as Tables 2 and 3 except that the former are for the years 2000 and 2005. In Table 18, we provide the complete regression results for the three-part model presented in Table 4. The estimated values of ρs are all highly statistically significant, indicating the relevance of allowing for the correlation in the error terms. The estimations for ρ_{dy} and ρ_{ds} are negatively significant at a 1 percent level from 2000 onwards. One plausible explanation is that the unobserved academic capability affects the enrollment and the other two decisions in different directions, possibly because very smart students need little spending on education. This possibility appears to be consistent with our estimate of ρ_{ys}, which is positive from 2000 onwards.

Table 19 shows that the regression results are similar when the independence of error terms is assumed. The sign and significance of the coefficients remain similar, but the absolute value of the coefficients for the conditional education expenditure and core share equations appears to be somewhat larger when the dependence structure is allowed for.

To understand the time trend of the gender bias in the education expenditure, we estimated the three-part model for all years simultaneously with the time fixed effects and their interaction terms with the girl dummy by pooling the four survey rounds. As the regression results in Table 20 show, the gender bias remains similar to the year-by-year results in Table 4. That is, enrollment decision is biased in favor of girls but the opposite is true for the conditional expenditure and core share decisions. Further, the coefficients on the interaction terms between the year and girl dummy variables show that the enrollment decision has become more profemale since the base year of 1995. On the contrary, the core share has become more promale. The bias in the conditional total education expenditure did not change much over time and, if anything, became more promale. Therefore, Table 20 indicates that the apparent contradirectional gender gap did not change much since 1995 and, if anything, strengthened by the fact that the profemale bias in enrollment decision and the promale bias in the conditional core share decision became stronger.

It may be argued that rural and urban samples should be analyzed separately, because there are various important differences between the urban and rural areas as mentioned at the end of Section 5. Further, as detailed in Section 6, the FSPs only covered nonmetropolitan areas. Thus, we re-estimate the analysis of the three-part model separately for the urban and rural areas. As the results in Table 21 show, the directions of the gender gap in the three equations are essentially the same except that they are less clear in 1995. The comparison between the urban and rural areas shows that the contradirectional gender gap in rural areas is generally stronger than that in urban areas.

Table 22 reports the marginal effect of being a girl at the sample mean for the secondary school enrollees for each item in education expenditure by Tobit regressions. Finally, Table 23 provides the marginal effects of the girl and FSP dummy variables at the sample mean for each education expenditure item. We only present the results for the years 2000 and 2005, because the FSP recipient status is either unavailable or irrelevant in other years (See footnote 21).

Table 16: Summary statistics of basic covariates by gender for 2000 and 2005 (secondary-school age group)

	2000				2005			
Variables	**Boy (B)** (1)	**Girl (G)** (2)	**G-B** (3)	**All** (4)	**Boy (B)** (5)	**Girl (G)** (6)	**G-B** (7)	**All** (8)
All children aged 11-15								
Enrolled in secondary school	0.331	0.444	0.113	0.386	0.407	0.509	0.102	0.457
	(0.471)	(0.497)	***	(0.487)	(0.491)	(0.500)	***	(0.498)
Child's age (yrs)	13.012	12.908	-0.104	12.961	13.079	13.001	-0.078	13.041
	(1.401)	(1.342)	***	(1.373)	(1.400)	(1.350)	**	(1.376)
HH per capita expenditure	10.722	11.419	0.697	11.064	14.296	14.717	0.421	14.504
(thousand BDT/year)	(7.809)	(9.013)	***	(8.428)	(10.282)	(11.578)		(10.943)
Household size	6.405	6.559	0.154	6.480	5.990	6.102	0.112	6.046
	(2.347)	(2.392)	**	(2.371)	(2.232)	(2.162)	*	(2.198)
Father's education (yrs)	2.841	3.104	0.263	2.970	3.045	3.186	0.141	3.115
	(4.130)	(4.198)	**	(4.165)	(4.187)	(4.208)		(4.198)
Mother's education (yrs)	1.725	1.939	0.214	1.830	2.224	2.322	0.098	2.272
	(3.095)	(3.198)	**	(3.148)	(3.501)	(3.532)		(3.517)
Number of children	3.533	3.635	0.102	3.583	3.243	3.336	0.093	3.289
	(1.741)	(1.758)	**	(1.750)	(1.568)	(1.584)	**	(1.576)
Urban	0.318	0.339	0.021	0.328	0.341	0.342	0.001	0.341
	(0.466)	(0.473)		(0.470)	(0.474)	(0.474)		(0.474)
Female head	0.073	0.080	0.007	0.076	0.095	0.093	-0.002	0.094
	(0.260)	(0.271)		(0.265)	(0.293)	(0.290)		(0.292)
Head is a wage worker	0.381	0.393	0.012	0.387	0.414	0.444	0.030	0.429
	(0.486)	(0.488)		(0.487)	(0.493)	(0.497)	**	(0.495)
Head's age (yrs)	46.988	46.877	-0.111	46.933	47.671	47.602	-0.069	47.637
	(10.738)	(10.957)		(10.845)	(10.623)	(10.445)		(10.535)
Muslim	0.919	0.922	0.003	0.921	0.890	0.893	0.003	0.892
	(0.272)	(0.268)		(0.270)	(0.313)	(0.309)		(0.311)
Hindu	0.076	0.071	-0.005	0.073	0.093	0.093	0.000	0.093
	(0.265)	(0.256)		(0.261)	(0.290)	(0.290)		(0.290)
Obs	2,488	2,390		4,878	2,848	2,790		5,638
Enrolled in secondary school children aged 11-15								
Govt school	0.25	0.23	-0.02	0.24	0.25	0.23	-0.02	0.24
	(0.44)	(0.42)		(0.43)	(0.44)	(0.42)		(0.43)
Private school	0.68	0.70	0.02	0.69	0.66	0.69	0.03	0.67
	(0.47)	(0.46)		(0.46)	(0.47)	(0.46)		(0.47)
Other	0.07	0.07	0.00	0.07	0.09	0.09	0.00	0.09
	(0.25)	(0.25)		(0.25)	(0.28)	(0.28)		(0.28)
Obs	824	1,061		1,885	1,159	1,420		2,579

Note: Standard deviations are reported in parentheses below the mean. ***, **, and * denote that the means for girls and boys are different at 1, 5, and 10 percent significant level, respectively. "Other" in school type include all schools other than public and private schools, including religious (e.g., madrasa) and NGO schools.

Table 17: Summary statistics of annual education expenditure in take by items for secondary school enrollees in 2000 and 2005

	2000				2005			
	Boy (B)	**Girl (G)**	**G-B**	**% Zeros**	**Boy (B)**	**Girl (G)**	**G-B**	**% Zeros**
BDT	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Core	2,116	1,681	-435	1	2,786	2,378	-408	1
	(2,092)	(1,723)	***		(2,452)	(2,405)	***	
Tuition	321	131	-190	48	374	162	-212	50
	(384)	(308)	***		(489)	(492)	***	
Private Tutoring	1,031	821	-210	49	1,438	1,289	-148	42
	(1,665)	(1,367)	***		(2,057)	(2,046)	*	
Material	764	729	-35	1	974	926	-48	1
	(527)	(486)			(589)	(579)	**	
Peripheral	918	878	-40	1	1,166	1,068	-99	0
	(930)	(901)			(1,383)	(1,103)	**	
Admission	170	152	-18	26	202	189	-14	26
	(233)	(218)	*		(310)	(349)		
Exam	152	143	-9	4	173	178	5	4
	(166)	(121)			(137)	(181)		
Uniform	239	257	18	46	343	344	1	35
	(315)	(292)			(450)	(391)		
Meal	176	176	0	63	193	155	-38	68
	(368)	(349)			(409)	(359)	**	
Transportation	121	111	-10	84	119	129	10	86
	(420)	(401)			(492)	(507)		
Others	60	38	-22	75	136	73	-63	66
	(312)	(214)	*		(794)	(251)	***	
Total	3,034	2,559	-475		3,952	3,445	-507	
	(2,665)	(2,319)	***		(3,127)	(2,979)	***	
Core Share	0.68	0.63	-0.05		0.69	0.65	-0.04	
	(0.18)	(0.20)	***		(0.18)	(0.19)	***	
Obs	824	1,061			1,159	1,420		

Note: Standard deviations are reported in parentheses below the mean. ***, **, and * denote that the means of girl and boy are different at 1, 5, and 10 percent significant level, respectively. The summary statistics is for the subsample of children who were enrolled in secondary school at the time of survey. Core share stands for the share of the core components in the total education expenditure. The annual session and registration fees are included in admission to maintain consistency with Table 3.

Table 18: ML estimation of three-part model with dependence for secondary-school age group

Coef.	1995			2000			2005			2010		
	d	Cond *y*	Cond *s*	*d*	Cond *y*	Cond *s*	*d*	Cond *y*	Cond *s*	*d*	Cond *y*	Cond *s*
Girl	-0.001	-0.085***	0.001	0.339***	-0.174***	-0.082***	0.291***	-0.154***	-0.071***	0.289***	-0.131***	-0.067***
	(0.042)	(0.032)	(0.032)	(0.039)	(0.049)	(0.014)	(0.034)	(0.027)	(0.012)	(0.033)	(0.025)	(0.009)
Log(per capita exp)	0.505***	0.755***	-0.326	0.480***	0.793***	-0.124***	0.374***	0.609***	-0.078***	0.357***	0.701***	-0.046**
	(0.047)	(0.043)	(0.261)	(0.050)	(0.052)	(0.041)	(0.044)	(0.034)	(0.027)	(0.046)	(0.034)	(0.022)
Log(hh size)	0.090	0.116*	-0.033	0.142*	0.222***	-0.014	-0.089	0.139***	0.025	0.124	0.317***	-0.049**
	(0.083)	(0.068)	(0.052)	(0.084)	(0.068)	(0.025)	(0.075)	(0.053)	(0.019)	(0.082)	(0.064)	(0.021)
Father edu (yrs)	0.081***	0.014**	-0.006	0.073***	-0.005	-0.008***	0.062***	0.006	-0.009***	0.039***	0.010**	-0.004***
	(0.007)	(0.006)	(0.006)	(0.007)	(0.011)	(0.002)	(0.006)	(0.005)	(0.002)	(0.006)	(0.004)	(0.001)
Mother edu (yrs)	0.088***	0.025***	-0.010	0.068***	-0.007	-0.008***	0.066***	0.023***	-0.009***	0.073***	0.017***	-0.008***
	(0.010)	(0.007)	(0.009)	(0.009)	(0.010)	(0.002)	(0.008)	(0.006)	(0.002)	(0.007)	(0.005)	(0.002)
No. of children	0.008	-0.004	-0.001	-0.026*	-0.022	0.003	-0.015	-0.024*	-0.006	-0.028	-0.021	0.009**
	(0.016)	(0.013)	(0.007)	(0.015)	(0.014)	(0.004)	(0.017)	(0.013)	(0.004)	(0.018)	(0.016)	(0.004)
Urban	-0.082	0.257***	-0.097	-0.121**	0.287***	0.000	-0.095**	0.275***	-0.011	-0.140***	0.233***	0.052***
	(0.053)	(0.045)	(0.091)	(0.048)	(0.046)	(0.020)	(0.040)	(0.030)	(0.016)	(0.040)	(0.029)	(0.012)
Female head	-0.038	-0.069	-0.019	0.106	0.004	-0.027	0.030	0.097*	0.016	-0.062	0.103**	-0.004
	(0.084)	(0.074)	(0.044)	(0.078)	(0.075)	(0.022)	(0.068)	(0.050)	(0.019)	(0.058)	(0.046)	(0.014)
Head is a wage worker	-0.103**	0.029	-0.044*	-0.201***	0.152***	0.028*	-0.210***	0.086***	0.037***	-0.145***	0.023	0.015*
	(0.049)	(0.041)	(0.023)	(0.045)	(0.052)	(0.014)	(0.038)	(0.030)	(0.011)	(0.038)	(0.029)	(0.009)
Head's age (yrs)	0.000	-0.003*	0.001	0.001	-0.005***	-0.001	-0.004**	0.001	-0.000	-0.004**	-0.003**	0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Muslim	-0.239	-0.138	0.079	0.219	0.128	0.143**	-0.073	-0.246***	0.000	0.199	-0.219*	0.039
	(0.244)	(0.138)	(0.075)	(0.312)	(0.186)	(0.064)	(0.167)	(0.094)	(0.045)	(0.211)	(0.123)	(0.052)
Hindu	-0.062	-0.128	0.086	0.306	0.263	0.140**	-0.132	-0.161	0.020	0.216	-0.189	0.070
	(0.253)	(0.144)	(0.075)	(0.318)	(0.197)	(0.067)	(0.177)	(0.101)	(0.046)	(0.217)	(0.128)	(0.053)
Secondary school accessibility	2.454***			5.940***			1.487***			2.501***		
	(0.606)			(1.019)			(0.364)			(0.447)		
Madrasa school accessibility	-0.287			-6.142***			0.274			0.763		
	(0.912)			(1.045)			(0.463)			(0.535)		
Public school		0.160			0.208**			0.135**			0.275***	
		(0.121)			(0.092)			(0.058)			(0.058)	
Private school		0.195			0.387***			0.286***			0.430***	
		(0.128)			(0.083)			(0.054)			(0.052)	
Log(education expend)			0.449			0.068			0.061			0.032
			(0.343)			(0.050)			(0.043)			(0.029)
σ_y		0.681***			0.740***			0.650***			0.671***	
		(0.017)			(0.056)			(0.017)			(0.015)	
σ_s		0.321*			0.242***			0.257***			0.235***	
		(0.190)			(0.013)			(0.010)			(0.010)	
ρ_{dy}		0.192**			-0.456**			-0.196***			-0.285***	
		(0.076)			(0.192)			(0.072)			(0.075)	
ρ_{ds}		-0.165			-0.829***			-0.935***			-0.894***	
		(0.116)			(0.081)			(0.025)			(0.029)	
ρ_{ys}		-0.810***			0.146			0.100			0.221**	
		(0.250)			(0.178)			(0.124)			(0.094)	
Observations		5,011			4,878			5,638			6,205	

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. School accessibility variables are the number of secondary schools or madrasa per 1000 people, which is calculated at the subdivision level (for 2000) or district level (for all other years). Age-specific fixed-effects terms are also included in each regression (not reported).

Table 19: ML estimation of the three-part model with different error structure

	d	Cond y	Cond s
1995			
Independence	-0.003	-0.086***	-0.030***
	(0.042)	(0.032)	(0.009)
Dependence	-0.001	-0.085***	0.001
	(0.042)	(0.032)	(0.032)
2000			
Independence	0.331***	-0.111***	-0.047***
	(0.041)	(0.032)	(0.009)
Dependence	0.339***	-0.174***	-0.082***
	(0.039)	(0.049)	(0.014)
2005			
Independence	0.309***	-0.131***	-0.027***
	(0.037)	(0.025)	(0.007)
Dependence	0.291***	-0.154***	-0.071***
	(0.034)	(0.027)	(0.012)
2010			
Independence	0.295***	-0.101***	-0.031***
	(0.035)	(0.024)	(0.006)
Dependence	0.289***	-0.131***	-0.067***
	(0.033)	(0.025)	(0.009)

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at household level are reported in parentheses. "Independence" rows are estimated under the assumption: $\rho_{dy} = \rho_{ds} = \rho_{ys} = 0$. "Dependence" rows are the same as those reported in columns (4)-(6) of Table 4.

Table 20: Results of the pooled regression using the three-part model

Coef.	*d* (1)	Cond *y* (2)	Cond *s* (3)
Girl	0.029	-0.097***	-0.032***
	(0.040)	(0.033)	(0.010)
Y_{00}	-0.036	0.224***	-0.017
	(0.039)	(0.035)	(0.011)
Y_{05}	-0.042	0.400***	-0.037***
	(0.040)	(0.032)	(0.013)
Y_{10}	-0.161***	0.541***	-0.054***
	(0.045)	(0.035)	(0.016)
Girl $\times Y_{00}$	0.317***	-0.059	-0.050***
	(0.055)	(0.047)	(0.015)
Girl $\times Y_{05}$	0.259*** (0.053)	-0.072*	-0.034**
		(0.042)	(0.014)
Girl $\times Y_{10}$	0.260*** (0.052)	-0.038	-0.032**
		(0.041)	(0.013)
Obs		21,732	

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. Additional controls include the set of covariates discussed in Table 4except that the school accessibility variables are constructed at subdivision level for all years to have a uniform definition across years. Year 1995 is the base year for comparison in these regressions.

Table 21: Estimation of the three-part model by the urban and rural subsamples

	Urban			**Rural**		
Coef.	*d*	Cond *y*	Cond *s*	*d*	Cond *y*	Cond *s*
1995						
Girl	0.094	0.008	-0.030*	-0.047	-0.131***	0.010
	(0.072)	(0.047)	(0.016)	(0.053)	(0.043)	(0.047)
Obs		1,695			3,316	
2000						
Girl	0.310***	-0.024	-0.047**	0.365***	-0.277***	-0.116***
	(0.073)	(0.053)	(0.021)	(0.047)	(0.059)	(0.019)
Obs		1,598			3,280	
2005						
Girl	0.264***	-0.102**	-0.054***	0.318***	-0.177***	-0.081***
	(0.060)	(0.046)	(0.016)	(0.042)	(0.034)	(0.016)
Obs		1,921			3,717	
2010						
Girl	0.376***	-0.095**	-0.069***	0.255***	-0.151***	-0.069***
	(0.057)	(0.043)	(0.015)	(0.041)	(0.032)	(0.011)
Obs		2,102			4,103	

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. The same set of covariates is used as in Table 4 except that the urban dummy is dropped.

Table 22: Tobit marginal effect of the girl dummy on education expenditure by expenditure item among secondary school enrollees

Expenditure in BDT	**1995**	**2000**	**2005**	**2010**
Core	-178.7***	-284.1***	-259.8***	-649.9***
	(62.7)	(70.9)	(77.4)	(137.6)
Tuition	-228.9***	-488.0***	-694.6***	-669.0***
	(26.6)	(38.4)	(60.8)	(63.5)
Private Tutoring	-142.7	-199.1*	-100.1	-578.8***
	(87.4)	(101.9)	(108.2)	(153.6)
Material	1.7	-5.4	-23.1	-14.9
	(19.3)	(21.1)	(20.5)	(31.1)
Peripheral	6.4	31.0	-45.0	59.8
	(35.1)	(37.5)	(45.5)	(69.6)
Admission	8.8	-20.5	-15.0	-26.9
	(11.5)	(13.0)	(15.5)	(24.8)
Exam	6.9	-2.3	9.6	-1.0
	(6.4)	(6.7)	(6.2)	(10.2)
Uniform	70.0***	86.5***	25.3	49.1*
	(22.7)	(22.5)	(23.8)	(25.9)
Meal	-310.6	44.9	-52.4	-59.5
	(840.1)	(37.4)	(40.7)	(57.7)
Transportation	9.2	-7.8	57.7	723.8***
	(65.8)	(95.3)	(109.7)	(187.7)
Obs	1,798	1,885	2,579	3,172

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. Marginal effects using Tobit regressions of education expenditure items evaluated at the mean of the subsample of secondary school enrollees are reported. The covariates are the same to those used in columns (2) and (5) of Table 4. The annual session and registration fees are also included in admission because they are not separately reported in HES 1995.

Table 23: Tobit regressions of education expenditure items for secondary school enrollees with the FSP dummy

	Marginal effects at the mean	**Core** (1)	Tuition (2)	Private Tutoring (3)	Material (4)	**Peripheral** (5)	Admission (6)	Exam (7)	Uniform (8)	Meal (9)	Transportation (10)
2000 Sec	FSP	-72.9	-518.2***	226.1	101.4***	125.5**	-69.5***	14.8*	95.2***	136.1**	283.4**
		(95.5)	(52.3)	(153.4)	(29.2)	(51.2)	(18.5)	(7.8)	(31.4)	(53.0)	(137.6)
	Girl	-240.5**	-207.7***	-337.4**	-66.0**	-44.1	20.9	-11.2	29.5	-39.1	-182.8
		(94.5)	(35.9)	(141.3)	(27.1)	(45.5)	(18.8)	(7.3)	(27.8)	(48.8)	(126.5)
	Obs	1885	1885	1885	1885	1885	1885	1885	1885	1885	1885
2005 Sec	FSP	-112.3	-704.9***	245.3	64.8**	4.7	-70.2***	1.7	61.3**	67.8	163.7
		(107.7)	(86.6)	(154.7)	(28.0)	(54.3)	(23.4)	(9.8)	(30.8)	(55.5)	(151.2)
	Girl	-202.1**	-383.7***	-228.7	-56.4**	-47.4	20.7	8.7	-6.4	-87.9*	-26.8
		(99.4)	(51.0)	(139.7)	(25.1)	(58.5)	(22.5)	(9.3)	(29.5)	(51.6)	(135.5)
	Obs	2579	2579	2579	2579	2579	2579	2579	2579	2579	2579

Note: ***, **, and * denote statistical significance at 1, 5, and 10 percent levels, respectively. Standard errors clustered at the household level are reported in parentheses. Marginal effects at the sample mean using Tobit regressions of each education expenditure item for the subsample of school enrollees are reported. The covariates are the same as those used in columns (2) and (5) of Table 4. The annual session and registration fees are included in admission to be consistent with Table 3.